

## From Marienthal to Latent Growth Mixture Modeling: A Return to the Exploration of Individual Differences in Response to Unemployment

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Job-loss is a rapidly growing concern as we witness the greatest and most rapid economic downturn in a century. The negative psychological effect of unemployment has increasingly garnered attention. Previous literature has offered a formidable prognosis, stating that in response to job-loss, people typically follow a pattern of rapid decline in life satisfaction and never return to preunemployment levels. In this paper, we attempt to search for individual differences in response to job-loss using Latent Growth Mixture Modeling (LGMM) framework. By building homogeneous trajectories within a prospective design from 3 years before to 4 years after job-loss, we find that the majority of individuals (82%) demonstrate no long-term effects on life satisfaction in response to unemployment. We also examine the roll of larger market forces on levels of life satisfaction during and around the event of job-loss. Using a correlation model, demonstrated that life satisfaction is positively influenced by the regional unemployment rate. Clark (2003) argues that people report higher well-being when they lose their job if those in proximity to them are also becoming unemployed. Using the national and local unemployment rate in a regression model nested in the Latent Growth Model, we found that a social comparison effect is present immediately before unemployment but not once individuals became unemployed. This implies that people reference national and local employment trends in an attempt to anticipate their own course of employment rather than referencing those trends after job-loss.

*Keywords:* Latent Growth Mixture Modeling, unemployment, life satisfaction

Losing a job can be a profoundly distressing event. As the United States and Western Europe experience unemployment rates approaching double digits for the first time in over 25 years, concern about unemployment has become ubiquitous. Unemployment has been shown to have a cost to the individual beyond the purely monetary concern of a loss in income. Nonpecuniary costs arise from unemployment as individuals potentially lose access to social relationships, identity in so-

ciety, self-esteem, and self-conception—all of which can be garnered from employment. Ultimately, even after reemployment, productivity, self-conception, cognitive efficiency, and attitudes toward work can continue to be affected (Darity & Goldsmith, 1996; Winkelmann & Winkelmann, 1998). In this paper, we investigate how unemployment, as well as broader economic trends during and before the event of unemployment, affects nonpecuniary costs.

A large body of literature argues that job-loss has a profound and long lasting detrimental psychological effect far beyond the generative effects associated with loss of income. The “psychological harm” of unemployment has been a long-standing area of interest and empirical study. Using a sociological framework, Johoda, Lazarsfel, and Zeisel (1933) studied the effects of unemployment in Marienthal, a small Viennese factory town, 3 years after the closing of the local factory.

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They described an observable malaise that could not be attributed only to a loss of income. Examples of this malaise after job-loss include declines in the use of public libraries, readership of free newspapers, membership in political organizations, and attendance at free events.

Contemporary researchers continue to be interested in the psychological harm associated with job-loss. Job-loss has been shown to negatively affect motivation, confidence, sense of control, and self-respect (Sen, 1997), and to negatively predict life satisfaction, even when controlling for fixed factors such as age, marriage, duration of unemployment, household income, and health (Winkelmann & Winkelmann, 1998). The costs to life satisfaction may continue even after reemployment. Multiple studies have demonstrated that an individual's level of life satisfaction declines after job-loss and does not return to prejob-loss levels after reemployment (Clark, Diener, Georgellis, & Lucas, 2008; Lucas et al., 2004). This may be because of the "scarring effect" of unemployment, a term referring to the empirically observed ongoing psychological harm caused by job-loss, even after the pecuniary effects have dissipated (Clark, Georgellis, & Sanfey, 2001).

Interestingly, other stressful life events have not been shown to have a long-term effect on life satisfaction. A large body of research has examined patterns of Subjective Well-Being (SWB) in response to major life events. In contexts other than unemployment, SWB has been shown to remain stable over time with only slight fluctuation surrounding major life events (Diener, Suh, Lucas, & Smith, 1999). Theorists maintain that fluctuations in SWB in response to major life events typically only last about 3 months (Suh, Diener, & Fujita, 1996). This pattern has been observed in response to events as varied as marriage, winning the lottery, surviving an accident, getting a divorce, or the death of a spouse (Brickman & Campbell, 1971; Brickman, Coats, & Janoff-Bulman, 1978; Suh, Diener, & Fujita, 1996). However, in the case of unemployment, the pattern of marked distress and rapid recovery does not appear to hold up.

How then do we reconcile these apparently contradictory findings? Is unemployment truly an anomalous case where the costs are so high that there is no recovery? We may find an explanation in the earliest empirical literature on unemployment. In the original Marienthal

study, three unique patterns of postjob-loss behavior were observed (Eisenberg, Lazarsfeld, 1938; Johoda et al., 1933): Those who refused to accept their current conditions and struggled to change them; those who were resigned, apathetic, indifferent, and without hope; and those who were characterized as anxious, bitter, and hopeless. Although Jahoda et al. (1933) did not operationalize these patterns with any precision, their key implication that there are varied responses to job-loss warrants further exploration.

### **From Mean Trajectories to Modeling Individual Differences**

Previous research on the effects of stressful life events has shown that utilizing group means ignores the heterogeneity intrinsic to the data and consistently results in underestimations of individual's ability to successfully adapt to stressful life events (Bonanno, 2004, 2005). Research on responses to unemployment has consistently utilized group means. However, as described by Johoda et al. (1933), responses to unemployment may be varied. Compelling evidence for heterogeneity comes from Georgellis, Gregoriou, Healy, and Tsitsianis's (2008) analysis of SWB in response to job-loss in the German Socioeconomic Panel Data (GSEPS). Utilizing nonlinear modeling, Georgellis et al. (2008) demonstrated diversity in the observed rate and degree of adaptation to unemployment. They concluded that linear regression models poorly fit the data and that the course of SWB in response to job-loss is best observed by exploring nonlinear patterns as well as heterogeneity.

Recent statistical advances now allow for the empirical exploration of the underlying heterogeneity of the data, which would otherwise be treated as error (Del Boca, Darkes, Greenbaum, & Goldman, 2004). Latent Growth Mixture Modeling (LGMM) has emerged as a particularly strong methodology for the study of homogeneous trajectories in a larger heterogeneous sample. LGMM allows for the modeling of longitudinal data with consideration for empirical observation as well as parsimony and interpretability (Jung & Wickrama, 2008). More specifically, LGMM tests whether the population under study is composed of a mixture of discrete classes of individuals with differing profiles of growth, with class membership determined by these different growth parameters.

Based on the heterogeneity observed by Georgellis et al. (2008), we expected that a single continuous distribution would be unlikely to fully represent individuals' responses to unemployment. Instead we hypothesized that a multiple trajectory model would better fit the data. Specifically, we used an LGMM approach to adjudicate the relative fit of one homogeneous pattern versus multiple homogeneous groups within a larger heterogeneous sample.

### **The Effect of Trends in Unemployment on Life Satisfaction**

Other research has demonstrated that life-satisfaction in response to job-loss varies in response to larger trends in the economy. Clark (2003) demonstrated that SWB was strongly positively correlated with regional unemployment rates, indicating that SWB in response to unemployment may be informed by comparison to social norms. Social norms are those beliefs held by societal members or relevant others (Akerlof, 1980). Unemployment itself can become normative as large portions of a given community lose their jobs. Clark argues that the psychological impact of one's own unemployment is affected as individuals compare themselves to those around them, and that individuals demonstrate a higher degree of SWB when their unemployment status is consistent with the surrounding community. Clark argues that while the pecuniary effects are the same, the normalization of unemployment informs the workers level of SWB and thus the nonpecuniary costs may not be as high.

We attempted to explore Clark's (2003) findings by examining the effects of national and local unemployment rates, both immediately before job-loss and after job-loss, in a regression model including other key covariates and nested within the LGMM model. By doing so, we can make inferences about causality rather than simply noting an observed relationship between variables. We hypothesized that individuals compare themselves both to local and national trends in unemployment before job-loss as they attempt to predict their own employment course in uncertain economic times.

Because we utilized a large representative sample in these analyses, rates of unemployment followed broader trends in the economy. Owing to the flexibility of the LGMM ap-

proach, we could examine how larger market trends affected SWB both in the years before and at the time of unemployment. As with the current economic climate, we reasoned that those still employed may anticipate the very real possibility of job-loss. As such, we predicted that these market trends would also have a profound impact on SWB before job-loss as well.

One of the more surprising findings in previous research is that even individuals who find new employment after losing a job continue to report diminished SWB relative to preunemployment levels (Clark, Georgellis, & Sanfey, 2001; Lucas et al., 2004). With this in mind, we examined how unemployment followed by re-employment might influence trajectories of SWB. We hypothesized that individuals who remained unemployed would demonstrate significantly lower SWB than individuals who found new jobs.

### **Method**

Participants for this study were part of the first 20 waves of the GSEPS from 1984–2003, a nationally representative study of German households identified through a multistage random sampling method ( $N = 16,795$ ) (see Haisken-De New & Frick, 2003). Data was collected through annual face-to-face interviews. Response rates were 60–70% and attrition was 3–13% per year. We focused on the subset of the sample that had reported unemployment, had been employed for a least three consecutive waves before unemployment, and had participated in the study for a minimum of four consecutive waves after the year of unemployment. In an attempt to avoid confounding unemployment with retirement, we limited the sample to individuals who had become unemployed before the age of 60. We also limited the sample to individuals who became unemployed at the age of 21 or older. Because this study focuses on the effects of unemployment on life satisfaction, we wanted to ensure that our sample only included individuals who had been in the job market for at least 3 years as opposed to individuals who were attempting to enter the job market. Our sample only included individuals who reported full time employment for a minimum of 3 consecutive years beginning at age 18 at the earliest, and was limited to individuals who became unemployed no later than the age

of 60. Individuals were only included if this was their first experience of unemployment since participating in the study. In addition, because we were explicitly interested in first responses to unemployment, we only examined individuals who displayed one spell of job-loss.

The sample had 774 participants (men 67%). Mean age at year of unemployment was 44.82 years ( $SD = 12.48$ ) and an income of DM 4,084 ( $SD = 2,745$ ). We analyzed 8 waves of data collected at yearly intervals (3 waves preevent, 1 wave the year of the event, and 4 waves postevent). Participants were organized around a “floating baseline” methodology where participants’ data was centered on the year of unemployment.

At each wave of data collection, a large number of demographic variables, including employment status, sex, age, level of education, and SWB were assessed. SWB was assessed based on responses to the question, “How satisfied are you nowadays with your life as a whole?” Respondents rated this question on a scale of 0 (completely dissatisfied) to 10 (completely satisfied).

## Analysis

Using Mplus 5.1, we used LGMMs to analyze the effects of job-loss from 3 years before the event to 4 years after the event to identify latent classes of unemployment response.

Our analysis of the effect of unemployment on SWB consisted of four steps. First, we iden-

tified a univariate single-class growth model without covariates to facilitate model specification for the LGMM. Second, we compared 1- to 5-class unconditional LGMMs (no covariates), assessing relative fit with conventional indices, including the Bayesian (BIC), sample-size adjusted Bayesian (SSBIC), Aikaike (AIC) information criterion indices, entropy values, The Lo-Mendell-Rubin likelihood test (LRT; Lo, Mendell, & Rubin, 2001), and the bootstrap likelihood ratio test (Nylund, Asparouhov, & Muthén, 2007). We sought a model with lower values for the criterion indices, higher entropy values, and a significant  $p$  value for the BLRT. Third, consistent with Flora’s (2008) recommendations for building and interpretation, we built a 3-piece piecewise model.

A piecewise model allows for greater dimensionality without a sacrifice to interpretability (Flora, 2008). Within a piecewise model, multiple progressive linear slopes can be modeled in the place of a single slope. Our piecewise model utilized three linear slopes, with one transition point between slopes at 1 year before unemployment and one transition point at 1 year after unemployment, as well as the point of comparison set at year 4 (year of job-loss). This allowed us to explore variability in SWB over the 3 years before job-loss, from 1 year before to 1 year postjob-loss, as well as variability in SWB after job-loss (see Figure 1).

Third, we assessed the effect of job-loss alone on SWB by introducing an extra growth factor in which SWB for the year of job-loss

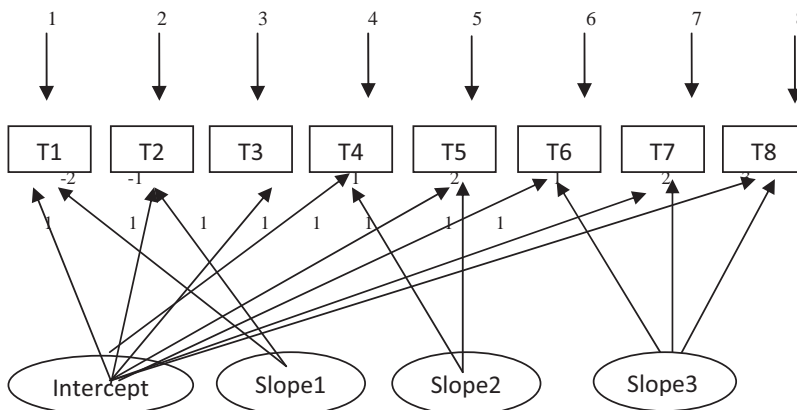


Figure 1. Three slope piecewise model.

was dummy coded. This allows us to examine if mean SWB within each class is significantly different from other time points. This is consistent with the literature for modeling the effects of particular salient moment in an LGMM framework (Greenbaum, Del Boca, Darkes, Wang, & Goldman, 2005).

Finally, national and regional unemployment rates at the year before job-loss and the year of job-loss as well as level of education and age were regressed on SWB as time variant covariates within classes. We also used a dummy coded variable indicating whether or not individuals had become reemployed by the year immediately after job-loss. Reemployment status and sex variables were placed in a logistic regression model predicting class membership, nested within the LGMM. By doing this, we can examine if people of one sex or employment status are likely to follow a particular pattern in response to unemployment.

## Results

First we constructed the strongest fitting unconditional model. An unconditional model is one that explores the number of latent classes and the characteristics of those classes without consideration of covariates. Next we constructed a conditional model. A conditional model is one which explores the significance of covariates on the aspects of the model. Covariates can be used to predict the slope, intercept, class membership, or variability in specific time points.

### Unconditional Model

The fit statistics for 1- to 5-class solutions are summarized in Table 1. The 2, 3, and 4 class

solution demonstrated improvements in the AIC, BIC, and SSBIC. Furthermore, the LRT and BLRT showed significant  $\chi^2$  difference from 1 to 2 to 3 to 4 classes. Entropy decreased slightly from 1 to 2 classes. However, entropy, a posterior probability of overall membership, remained within a high range consistent with Muthén's (2003) recommendations. Model improvement was observed from 1- to 4-class solutions in all indicators with the exception of entropy. However, moving from a 4 to 5 class solution, the LRT and BLRT demonstrated non-significance  $\chi^2$  (LRT  $p_{rep} = .49$ ; BLRT  $p_{rep} = .75$ ). Following recommendations for a best fit solution (Muthén, 2003), we proceeded to the conditional model with a 4 class solution.

We then compared models with fixed linear weights, quadratic weights, a freely estimated model, and a three slope piecewise model. Based on a comparison of the AIC, BIC, SSA-BIC, and entropy, we retained the piecewise model. Compared to the previously best performing model, the freely estimated model, the piecewise model demonstrated a reduction in the AIC (200.57); BIC (75); and SSA-BIC (160.75), and demonstrated a higher level of entropy than any previous unconditional models—entropy (.84).

The majority of participants (High-Stable, 69%) were assigned to a class with a slight but significant negative slope from 3 years to 1 year before job-loss and a relatively stable levels of SWB from 1 year before to 4 years postjob-loss as indicated by nonsignificance across slopes 2 and 3 ( $\beta_{s1} = -0.32$ ,  $SE = 0.08$ ,  $p < .001$ ;  $\beta_{s2} = -0.08$ ,  $SE = 0.09$ ,  $p = .38$ ;  $\beta_{s3} = -0.07$ ,  $SE = 0.05$ ,  $p = .17$ ). Based on the estimates of the separate growth parameter, we observe that mean levels of SWB are significantly lower than

Table 1  
*Fit Indices for 1 to 5 Class Growth Mixture Models of Unemployment (Unconditional)*

Fit indices	Growth mixture model				
	1 Class	2 Classes	3 Classes	4 Classes	5 Classes
AIC	23,500.41	22,136.05	21,815.05	21,683.94	21,643.65
BIC	23,519.01	22,182.55	21,880.17	21,767.68	21,745.98
SSBIC	23,506.31	22,150.80	21,835.72	21,710.52	21,676.12
Entropy	—	.83	.76	.77	.78
LRT $p$ value	—	<.001	.001	.02	.52
BLRT $p$ value	—	<.001	<.001	<.001	.17

Note. AIC = Akaike information criterion; BIC = Bayesian information criterion; SSBIC = sample size adjusted Bayesian information criterion; LRT = Lo-Mendell-Rubin test; BLRT = bootstrap likelihood ratio test.

other time points for people in this class loss ( $\beta = 1.38$ ,  $SE = 0.63$ ,  $p < .05$ ). This indicates that individuals in this class are significantly negatively affected by the event of job loss, but recover to preloss levels of SWB fully by the following year.

The second largest class (Improving, 15%) demonstrated an increase in SWB before job-loss, a flat slope in response to job-loss, and a flat slope from 1 to 4 years after job-loss ( $\beta_{s1} = 0.88$ ,  $SE = 0.27$ ,  $p < .01$ ;  $\beta_{s2} = 0.23$ ,  $SE = 0.22$ ,  $p = .30$ ;  $\beta_{s3} = -0.24$ ,  $SE = 0.17$ ,  $p = .16$ ). Based on the estimates of the separate growth parameter, this class also showed a significant decline in SWB in response to job-loss ( $\beta = 1.96$ ,  $SE = 0.85$ ,  $p < .05$ ). However, as with the High-Stable class, levels of SWB were not significantly different from 1 year before to 1 year after job-loss.

The third largest class (Low-Stable, 13%) demonstrated three flat slopes; however, they also demonstrated a much lower starting point in SWB than the high functioning class ( $\beta_{s1} = -0.08$ ,  $SE = 0.35$ ,  $p = .83$ ;  $\beta_{s2} = -0.36$ ,  $SE = 0.30$ ,  $p = .23$ ;  $\beta_{s3} = 0.31$ ,  $SE = 0.21$ ,  $p = .14$ ). Furthermore, the separate growth parameter indicates that SWB for the year of unemployment did not vary significantly from SWB at other time points indicating that SWB for the year of job loss was not significantly different from SWB at other time points.

The smallest class (Distressed, 4%) showed a significant and noticeable decline in response to

job-loss, and although their level of SWB showed improvement demonstrated by a positive slope after job-loss, the third slope was less pronounced and these individuals never fully returned to preunemployment levels of SWB ( $\beta_{s1} = -0.18$ ,  $SE = 0.21$ ,  $p = .39$ ;  $\beta_{s2} = -2.52$ ,  $SE = 0.45$ ,  $p < .001$ ;  $\beta_{s3} = 1.35$ ,  $SE = .32$ ,  $p < .001$ ) (see Figure 2). As with the previous class, the separate growth parameter indicates that SWB for the year of unemployment did not vary significantly from SWB at other time points indicating that SWB for the year of job loss was not significantly different from SWB at other time points.

### Conditional Model

Regional and national and unemployment rates at year before and at the year of unemployment, age, and educational level at the year of job-loss, were regressed as time variant covariates on SWB between classes at the corresponding time points. The addition of the covariates did not change the trajectory patterns from the unconditional model, and percentage of group membership from the unconditional model changed only slightly. See Figure 2 for the conditional class structure.

The national and regional unemployment rates at the year of unemployment were not significant predictors of SWB during the year of unemployment across classes ( $\beta_{national} = 0.05$ ,  $SE = 0.05$ ,  $p = .30$ ;  $\beta_{regional} = -0.03$

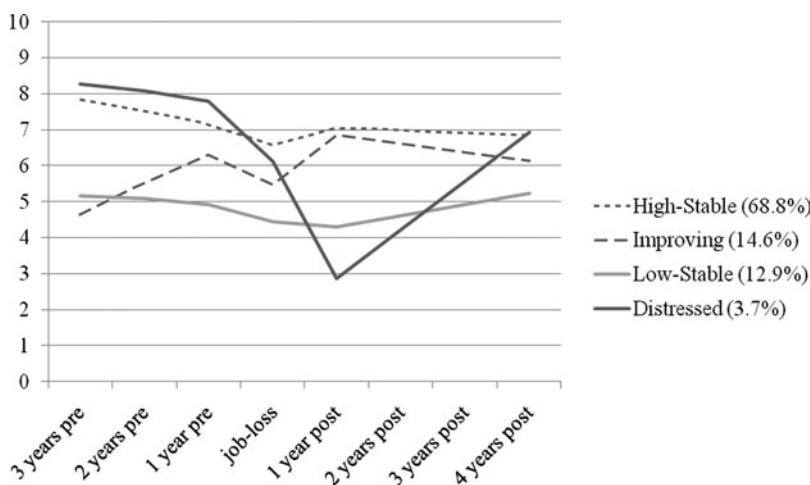


Figure 2. Four class growth mixture model with covariates.

$SE = 0.03, p = .31$ ). When these variables were used in a correlational model, we found similar results to Clark (2003). This indicates that although Clark (2003) observed a correlation between unemployment rates and SWB, when nested in a more complex model, no causal relationship is observed. The national and regional unemployment rates for the year before job-loss both demonstrated significance ( $\beta_{national} = 0.05 SE = 0.02, p < .05$ ;  $\beta_{regional} = -0.06 SE = 0.02, p < .01$ ). This indicates that once we account for market trends in our model before the event of job-loss, the social comparison effect observed by Clark (2003) is better explained as a comparison before the event. Furthermore, SWB appears to respond quite differently to national versus regional market trends in employment. Based on the directionality of the  $\beta$ 's, we observe that just before job-loss, people compare themselves positively to high national unemployment trends but compare themselves negatively to regional unemployment trends.

The other time variant covariates (age, level of education) demonstrated mixed results. Level of education did not significantly predict level of SWB in response to job-loss, indicating that job-loss is equally trying for individuals of all educational levels ( $\beta = -.04 SE = 0.03, p = .25$ ). However, age did enter into the model as a significant positive predictor ( $\beta = 0.02 SE = 0.005, p < .001$ ). This indicates that with age comes a less significant drop in SWB in response to job-loss.

We also included a logistic regression model nested in the LGMM with covariates (sex, re-employment status) predicting class membership. The logistic regression demonstrated mixed results. Sex did not enter as a significant predictor of the differences between any of the four classes. Reemployment status demonstrated a marginal effect in differentiating between individuals in the High-Stable and Low-Stable classes ( $\beta = -0.83 SE = 0.52, p = .11$ ) as well as the Low-Stable and the Distressed ( $\beta = -1.30 SE = 0.13, p = .09$ ). A significant difference was observed between the Low-Stable class and the Improving class ( $\beta = -1.46 SE = 0.55, p < .05$ ). All of the above indicate that the Low-Stable class is least likely to be reemployed after job-loss. The significant difference between the Improving and the Low-Stable may indicate that reemployment plays a

significant role in distinguishing trajectories of SWB after job-loss.

## Discussion

We modeled multiple trajectories of SWB from 3 years before to 4 years after job-loss using a large representative sample covering the years 1984 to 2003. Previous findings using the same data with a single trajectory model have shown that people's level of SWB drops significantly after job-loss, never to recover (Clark et al., 2008; Clark et al., 2001; Lucas et al., 2004). By using an LGMM approach influenced by an individual differences theoretical framework, we were able to identify four distinct homogeneous response patterns that statistically fit the data better.

The four classes presented in this paper indicate that responses to unemployment do not represent a unified phenomenon as previously believed. Rather, our analysis indicated four prototypical patterns of response over time, the most common of which is characterized by a high degree of stability in SWB from before to after job-loss (High-Stable, 68.8%). A smaller class of individuals (Improving, 14.6%) demonstrated a positive trend before job-loss, and a flat slope from 1 year before to 1 year after job-loss. These individuals appear to have been on a positive trajectory that was temporarily stifled by the aversive affects of job loss. Importantly, this class regained its positive trend in SWB within a year of having lost a job. The third largest class of individuals (Low-Stable, 12.9%) was characterized by three flat slopes of consistently low SWB. This group essentially evidenced a floor effect in subjective well-being and did not appear to respond specifically to job loss. Finally, the smallest class of individuals (Distressed, 3.7%) showed a consistently high level of SWB for 3 years before job loss, a steep decline with job-loss, and then 1 year after job loss, a gradual incline in SWB. Four years postjob loss, however, this class had still not returned to their baseline prejob loss levels of SWB (see Figure 2).

### Before Losing a job

We explored the role of larger market trends (regional and national unemployment rates) on SWB both for the year of and the year before

job-loss. Specifically, we explored the effect of these variables on SWB in the context of a more complex regression model, nested in the larger LGMM while accounting for other salient predictors of SWB (age, level of education). When exploring simpler correlational models, we found similar results to Clark (2003), which demonstrated a strong positive relationship between SWB and regional unemployment rates. Clark explained this phenomenon in terms of social comparison, where SWB is higher if others are going through similar employment problems. By building a model that accounted for rates before job-loss, we found that regional and national unemployment rates predicted SWB before job-loss but had no effect once job-loss had occurred. Because we are using a large representative sample of individuals who lost jobs, we can predict that many of them lost jobs in response to market trends. As such, they may have been reasonably concerned about retaining employment as they watched both regional and national market characteristics change to their disadvantage. This is most pronounced in the largest class (High-Stable), which demonstrates a negative slope in SWB before job-loss, but not during or after. This anticipatory effect appears to have a much more profound impact on SWB than the effects of those trends after one has already lost their job. We observe that in the year before job-loss, people compare themselves positively to national trends, but negatively to regional trends. This may indicate that as larger national trends are observed, people are likely to feel grateful that they are unaffected. However, as unemployment comes home to their own community, they may be more likely to worry that they are next to lose their job.

### **Losing a Job**

To say that most individuals recover to baseline levels over time is not to say that losing a job does not have strong detrimental effects on SWB. By creating a separate growth parameter, we can observe that for most individuals, SWB declines significantly immediately after losing a job. The only group that does not demonstrate a drop in SWB in response to job-loss is a small class of individuals (Low-Stable) who may be characterized by a continuous floor effect in SWB across all time points. An analogy may be

that if an individual is severely depressed already, it may be hard to see the negative psychological effects of a particular event.

We chose to build a nested regression model to explore the effects of age and level of education together. Interestingly, we found that while people of different levels of education fared the same, younger people responded worse to unemployment. The fact that older people respond better to job-loss may imply that with more experience comes less impact of negative events such as job-loss.

### **Regaining Employment**

We found that people who were unable to regain employment within a year were most likely to be in the Low-Stable class, a class characterized by an extremely low level of SWB over all eight time points. As individuals in this class consistently demonstrated low levels of SWB before job loss, this may be strong indication that psychological factors do play an important role in employment characteristics. Perhaps equally interesting, we observe that people in the other three classes are no more or less likely to regain employment. This indicates that reemployment alone is not accounting for the observed trends in SWB after job-loss.

### **Conclusion**

In this paper, we explored the effects of job-loss on SWB from 3 years before unemployment to 3 years after unemployment. Our findings indicate that the responses to job-loss do not represent a unified phenomenon and as such are poorly represented by a single trajectory that models the mean. Consistent with previous research (Clark et al., 2008; Lucas et al., 2004), we found that if we examine a single mean response pattern, we find that on average people's SWB dips severely in response to unemployment and never returns to preunemployment levels even years after the events. However, by modeling multiple homogeneous patterns of response, we find that the vast majority (68.8%) cope well with this event, showing little long-term perturbation in SWB. We also find that for the vast majority of individuals, a drop in SWB in response to job-loss is transient as people return to previous levels by 1 year postjob-loss.



We also found that broad economic patterns have a strong effect on SWB before but not during job-loss. We observed a positive relationship between national unemployment rates and SWB and a negative relationship between regional unemployment rates and SWB in the year before the event of job-loss. This indicates that individuals do attend to larger trends in unemployment in very different ways. These findings may indicate that as people observe national trends while retaining their jobs, they are less concerned about the effects and may even feel as if they have dodged the job-loss bullet. However, when job-loss comes home and is observed in their community, their SWB drops significantly in anticipation of the inevitable event of job-loss. This anticipatory effect is also observed in the class structure itself. The largest class demonstrates a significant decline in SWB before unemployment. This decline may best be explained by a realistic anticipation of job-loss.

The nature of the sample comes with built-in methodological shortcomings that must be noted. In particular, because we used a large representative sample, we do not have information on why these individuals lost their job. Furthermore, we observe a causal relationship between market trends and SWB and discuss this relationship in terms of social comparison. However, further information is needed to make this claim definitively. Further research in this area is necessary to elucidate the relationship between broader market trends and attitudes about job-loss.

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