High-Risk Violent Prisoners' Patterns of Change On Parole on the DRAOR's Dynamic Risk And Protective Factors

Devon L. L. Polaschek and Julia A. Yesberg

Victoria University of Wellington

New Zealand

Author Note

Devon L. L. Polaschek & Julia A Yesberg, School of Psychology, Victoria University of Wellington.

Julia Yesberg is now employed by the Mayor's Office for Policing and Crime, London

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Correspondence concerning this article should be addressed to Devon Polaschek, School of Psychology, The University of Waikato, Private Bag 3105, Hamilton 3283, New Zealand. E-mail Devon.polaschek@waikato.ac.nz

Abstract

Few studies have examined change after treatment completion, despite the potential for such investigations to enhance our understanding of how a rehabilitative intervention leads to reduced recidivism. Newer statistical tools make it possible to describe and analyze patterns of change over multiple measurements, even with missing measurements and variable measurement intervals. The current study provides an example of the application of growth curve modeling in the context of assessing change in dynamic risk factors. We examined patterns of change in the community, following two samples of high-risk men for up to 12 months on parole; one had completed intensive psychological treatment, and the other completed no programs or briefer programs in prison. As expected, intensive program completers entered the community with higher protective factors and lower stable and acute dynamic factors, and showed less variability on acute risk factors, as did all of those with better initial scores. However, the two samples improved at a similar rate over the course of parole. Those with initially poorer scores changed less on parole except for protective factors; those with stronger initial protective scores showed less change.

Introduction

Criminal risk prediction entered a new era when risk factors with the potential to change were included in assessment tools. There are four main reasons why these dynamic risk factors (DRFs) offer an advantage over the sole use of static, unchangeable or history-based factors. First, DRFs can document risk-related change during or following periods of intensive intervention; making them useful both for adjusting an offender's risk and for establishing who responds to intervention, and how. For example, recent research with the dynamic subscales of both the Violence Risk Scale (VRS; Wong & Gordon, 2006) and its sex offender version (VRS:SO; Wong, Olver, Nicholaichuk, & Gordon, 2003) show that scores on both the dynamic factors scale, and the overall level of change made by offenders during treatment on that same scale are predictive of relevant recidivism outcomes (Lewis, Olver, & Wong, 2013; Olver, Wong, Nicholaichuk, & Gordon, 2007). Second, DRFs offer a more personalized or idiographic assessment of the domains that comprise a person's overall estimated risk level; an instrument based on DRFs will identify which factors are relevant for that person and which are not.

Third, DRFs may not be strictly causal, but they are at least more psychologically meaningful than history alone (Mann, Hanson, & Thornton, 2010). They help to unpack the bases for the predictive power of static factors, and thus have much more potential for bottom-up theory development. In other words, static risk factors function as proxies for explanatory psychological variables they correlate with. For example, why is young current age a risk factor for offending? Presumably because it is standing in for processes that become weaker or stronger with age and have more theoretical explanatory depth, such as being more strongly influenced by criminal peers, being more likely to abuse alcohol and drugs, and having poorer affect regulation when young. Most static factors are indices of a history of behavior. That behavior tends to be somewhat consistent over time is useful, but what is more useful for theory and intervention development is understanding why consistency occurs. This is where DRFs come in. Fourth, DRFs may vary in how rapidly they change (see below). The more rapidly changing factors may provide “real-time” information for making day-to-day adjustments in offender management; thus offering unlimited micro-intervention opportunities.

The overall potential of DRFs is far from being fully recognized; there is limited research on all four of these characteristics. The research described here mostly addresses the first and third of these potential contributions: we report results based on multiple measurements with a dynamic risk prediction tool, comparing high-risk intensively treated and treatment-as-usual samples of male prisoners, after release into the community.

How Does Treatment Effect Change?

Considerable advances have been made in understanding the constituent principles of interventions that can reduce reconviction risk (the “what works” research, and the principles of the Risk-Need-Responsivity model; Andrews & Bonta, 2010). In a large meta-analysis, adherence to all three Risk, Need and Responsivity principles resulted in a mean effect size of .28 (i.e., if recidivism in the untreated group was 50%, it would be 22% for the treated group; Andrews & Bonta, 2010). By comparison, an effect size of .05 was found for non-adherence to any of the principles. Numerous independent meta-analyses confirm the effectiveness of correctional treatment that is based on human service, and follows the general principles codified by Andrews and Bonta[1]. But much less progress has been made in understanding how such programs alter outcomes for individual offenders on the way to recidivism or desistance. One major method for understanding the effects of treatment is through examination of how dynamic risk factors change as part of treatment participation (see also Serin, Lloyd, Helmus, Derkzen, & Luong, 2010). However, another important and usually overlooked source of information comes from how offenders progress after treatment.

[1] More than a decade ago, McGuire (2004) listed 40 such meta-analyses.

Theories of how cognitive-behavioral treatment programs for offenders effect change are generally not well articulated. Practitioners commonly accept the basic idea that making positive changes in the cognitions and behavior that underpin dynamic risk (e.g., thinking and behaving more constructively, prosocially or skillfully) will ultimately lead to desistance. Such changes are usually theorized to begin in the program itself, partly as a function of training participants in methods of change, and then providing opportunities to observe and practice new behaviors in a change-supportive environment. But changes then need to generalize to other environments such as mainstream prison units or community settings, where skills may no longer be reinforced or may even be actively punished, and where self-control over old criminogenic habits may be threatened (Day & Casey, 2010; e.g., by exposure to well-established external risk factors such as criminal peers, or drug and alcohol accessibility). Understanding what is needed for change in any setting remains subject to debate (Evans, 2013). Cognitive-behavioral approaches to offender rehabilitation leave unclear whether successful treatment results in a generalization of end-of-treatment behavior to other settings, or whether there is an expectation that changes begun in treatment will continue to evolve in form.

Dynamic Risk and Protective Factors, and Change Following Treatment

Patterns of change *following* treatment have almost never been examined with offenders (See Stirpe, Wilson, & Long, 2010 for an exception). A failure to examine whether dynamic risk factors remain lower, or even reduce further after treatment may be especially important in light of a recent small-scale investigation of post-treatment effects of intensive psychological rehabilitation of high-risk violent prisoners. Based on a sample of life-sentenced men who remained in prison after treatment completion, we found that change during treatment was unrelated to change over the first year after treatment (measured using Wong and Gordon's [2000] VRS; Yesberg & Polaschek, 2014). We also found that high-risk treatment completers left prison on average only in the *Preparation* stage of change on their treatable dynamic risk factors (Polaschek, Yesberg, Bell, Casey, & Dickson, 2015). A VRS-based rating of Preparation indicates that the person is exhibiting observable behavioral change relevant to various DRFs but has not shown consistent change over a sustained period: sometimes lapsing back into old patterns. It follows that if prisoners are released in these fragile early stages of observable behavior change, maintaining and even generalizing these changes in a much less supportive environment will be a big challenge. Measuring change beyond treatment and release may inform our understanding of the longer-term effects of treatment.

One of the most theoretically important yet simple distinctions made regarding DRFs has been between stable and acute risk factors. Zamble and Quinsey's (1997) coping-relapse model of recidivism distinguished between relatively enduring but changeable offender attributes (e.g., criminal beliefs, emotional regulation skills, balance of antisocial and prosocial peer influences, work ethic), and acutely destabilizing antecedents in the environment (e.g., loss of job, fight with domestic partner, loss of key prosocial support) and in the offender's responses (getting drunk, getting angry, behavioral dysregulation, low mood), which they noted could be "often labile or transitory" (p. 6). This distinction is not only theoretically important, but also reflects the importance of understanding highly variable states and more stable trait-like factors that may contribute to them. According to Zamble and Quinsey, the temporal process leading to reoffending is set in train by an environmental trigger, that can set off a cascade of offender responses. The triggering ability of that environmental event is a result of its interaction with stable dynamic risk factors within the person. This theory suggests that those managing an offender during re-entry should attend both to rapid risk management responses when acute triggers are detected, and to ameliorating stable factors to reduce their ability to interact with environmental triggers.

Etiological theories of risk for sexual offending also distinguish between more enduring psychological vulnerabilities, and risk states in which those vulnerabilities may have been triggered by contextual factors (Beech & Ward, 2004) This acute-stable distinction is reflected in some newer assessment tools (e.g., Stable-2007 and Acute-2007; Hanson, Harris, Scott, & Helmus, 2007; Hanson, Helmus, & Harris, (2015).

Newer tools oriented toward protective factors have also emerged (e.g., the SAPROF; Vries Robbé & Vogel, 2011), and as with dynamic risk factors, both protective factors themselves, and changes in dynamic protective factors have been demonstrated to predict recidivism (Vries Robbé, Vogel, Douglas, & Nijman, 2015). There is some confusion in the current literature about the nature and definition of protective factors relative to risk factors. Protective factors are sometimes defined as moderators of DRFs (i.e., they may have an important buffering effect if a high level of a DRF is present but are irrelevant if it is not). More often they may simply be reverse-worded—and therefore reverse-scored—dynamic risk factors. In this situation, the main purpose of the focus on protective factors is not empirical but practical: to orient practitioners more toward those factors that are relative strengths (i.e., areas that don't need attention, or are worthy of further strengthening; Polaschek, 2016). For example, poor affect regulation and good affect regulation are respectively a DRF and a protective factor.

Some of these distinctions—between stable, protective, acute environmental, and acute within-individual factors—may have implications for understanding treatment effects. Although treatment is expected to reduce stable dynamic risk factors, its impact on protective factors, particularly if it is an RNR-based treatment has been postulated by some to be limited (Ward & Brown, 2004). Furthermore, if treatment does reduce stable dynamic risks, what effect does that reduction have on acute risk levels? Although not explicitly stated by theorists, a coping-relapse model of recidivism such as that posited by Zamble and Quinsey (1997) might lead to the prediction that lower stable DRFS will be associated with fewer circumstances in which acute risk factors are triggered (Hanson et al., 2007), and further, that the effects of treatment may be seen in greater stability in dynamic risk factors over time.

The Current Study

This study reports an examination of change patterns in two samples released onto parole, from a previously reported longitudinal study (Polaschek et al., 2015). The main data here were derived from multiple assessments conducted by probation officers meeting regularly with these high-risk parolees, and monitoring them in the community using the Dynamic Risk Assessment for Offender Re-entry (DRAOR; Serin, 2007). In the first part of the analyses, we tested two hypotheses: (a) that completers of the intensive prison-based treatment programs would score significantly lower on acute and stable dynamic risk factors and higher on protective factors at release; and (b) that if so, treatment completers would show less variability in their rate of change, especially in acute risk factors than less treated comparisons. We also explored whether acute factor variability was related to initial levels of stable and protective factors more generally. Because of the lack of clarity in the treatment literature about post-treatment patterns of change, we had no clear hypothesis about whether treatment men would continue to change over time after release, or simply would maintain the change already made before release. Similarly, if a positive change trend was found, the literature was unclear about whether it would be greater for treatment vs. comparison men. Therefore, other than for hypothesis (b) above, change pattern analyses were exploratory.

Most risk-related change assessment studies are based on just two data points: most often in the context of pre-post treatment change evaluations (e.g., Olver, & Wong, 2013). More recent risk assessment tools that are designed for multiple administrations (e.g., Stable-2007 and Acute-2007; Hanson et al., 2007; OASys OVP; Howard & Dixon, 2013; DRAOR; Serin, 2007) pose significant challenges to traditional statistical techniques (e.g., repeated measures ANOVAs). Multiple repeated measures using a single tool offer an opportunity to study patterns of change in a more nuanced and reliable manner than is possible with just two measurement points. Newer statistical techniques such as growth models (also called latent growth curve models, hierarchical linear models, multi-level models), although still rarely used in correctional data analysis, are ideally suited to multiple time-point data. They can handle common challenges with longitudinal data: missing measurements for some individuals at some points in the sequence, variable time intervals between measurements, and variable sequence lengths for each individual (Yang, Guo, Olver, Polaschek, & Wong, 2015). They are a series of methods that allow us to explore inter-individual differences in longitudinal within-person change patterns, and often with greater statistical power than the more conventional alternatives.

In the second part of the analyses, we used Growth Curve Modeling to provide a preliminary picture of change after re-entering the community: exploring patterns of change in DRAOR scores for up to 12 months after release. We were particularly interested in examining whether intensive treatment resulted in more rapid positive changes in risk and protective factors than for those in the comparison group. Faster changes in dynamic factors might be expected if the effects of, for example, treatment-related skill development led to accelerated progress after treatment.

Method

Participants

All participants in this study were serving sentences of at least two years in prison, during which about half completed an intensive psychological treatment program (the Treatment sample), while the other half completed less intensive or no rehabilitative interventions (the Comparison sample). People sentenced in New Zealand to two or more years in prison are legislatively required to undertake a period of parole supervision following release. The minimum period of parole of six months applies to those released at the end of their sentence. However, prisoners are eligible for consideration for early parole at any point after they have completed the first third of their sentence[2]. The national parole board decides the timing of release based on factors that include estimates of current dynamic risk and the quality of the release plan, and just prior to release—whether early or at the end of the prison sentence given—they set release conditions that may include assessment and/or treatment with a psychologist, or alcohol and drug counsellor, curfews and restrictions of movement and association. Following release, each is assigned a specific community probation officer who is directly responsible for ensuring parole license conditions are fulfilled. Initially, parolees report to these officers at least once per week; the officers complete the DRAOR (see below) and otherwise monitor and support the offender in complying with his sentence and in successful community reintegration.

Treatment Sample

Treated offenders were 151 men recruited from the pool of prisoners who completed cognitive-behavioral treatment at one of New Zealand's four high-risk special treatment units for male prisoners (HRSTUs; see Polaschek & Kilgour [2013] for a full description). Men who enter these units have, prior to treatment, an estimated risk of returning to prison of at least 70% over the five years following release[3], are serving imprisonment sentences of at least 2 years, are over the age of 20, have a low-medium or minimum security rating[4], have sufficient time left on their sentence to complete the program, and agree to be transferred to a program unit. About two-thirds of those who start complete the program. Participants in this research were recruited just

[2] Those released before the end of their original prison sentence usually have a total period on parole that represents the remaining time left to serve in prison, plus six months. On average prisoners are currently serving about 70% of their sentence, with about one-third serving the whole sentence prior to release (personal communication, P Johnston, 11 March, 2016).
[3] According to the RoC*RoI: the New Zealand Department of Corrections' tool for actuarial risk assessment (see description in Measures section)
[4] NZ prison security classifications are determined by a points-based system that gives scores for both internal (risk to prisoners and staff) and external security risk (risk to the community if he escaped). Points are awarded based on a prisoner's offence history but also on his conduct in prison during the current sentence. High-risk offenders have a high likelihood of reoffending in the community, but because the anticipated offence may not necessarily be serious, and if the offender has shown sufficiently good behaviour in prison, a high-risk offender may work his way through the security ratings and be released from low-medium or even minimum security.

prior to release on parole. They were released into the community between December 2010 and November 2013. Their demographic characteristics are reported in Table 1.

The HRSTUs aim to treat about 120 high-risk violent male prisoners each year. They provide a structured, closed-group cognitive-behavioral therapy intervention within a modified democratic therapeutic community, tailored to recognize a majority referral population of Māori and Pasifika prisoners. The core treatment program is delivered to groups of 10 men by pairs of facilitators. One member of the pair is usually a psychologist, while the other facilitator usually has a background in a related field (e.g., education, social services). Facilitators have a range of cultural backgrounds and may be any gender.

Men attend group sessions for approximately 250 hours over 25 weeks, and remain in the treatment unit for 10-12 months (Polaschek & Kilgour, 2013). The group sessions focus on a variety of areas including offense-supportive thinking, mood management, problem solving, drug and alcohol problems, and relationships/communication. The final part of treatment focuses on preparing men for release. In addition to basic release planning (i.e., where they will live, who will be their support network), offenders develop a personalized safety plan where they identify potential high-risk situations and develop strategies to effectively manage them. Outcome evaluations from the HRSTUs have been positive overall (Kilgour & Polaschek, 2012; Polaschek, 2011; Polaschek et al., 2015). The most recent evaluation—based on the current dataset—found a significant reduction in recidivism within one year after release for HRSTU completers compared with the comparison sample (Polaschek et al., 2015).

Comparison sample

The comparison sample (*n* = 153) was recruited from men who met the referral criteria for the HRSTUs but who had not been treated there. Some of the documented reasons for not attending included: lack of time left in sentence, disinterest in the program, reluctance to sever geographical ties to family, employment, lack of awareness about the program, and participation in other programs. With only a small number of places available in the HRSTUs each year relative to referral eligibility, most eligible high-risk violent offenders during this period were released onto parole without attending HRSTU treatment. In other words, failure to attend did not necessarily appear to be a function of a lack of motivation to undertake HRSTU or any treatment. But comparisons were not necessarily ‘untreated’. When interviewed, 77% reported that they had taken part in some form of program on their current prison sentence (e.g., individual psychological treatment, specialized substance dependency treatment; see Polaschek et al. [2015] for more detail). Table 1 describes key demographic and offense history characteristics of the sample.

Measures

The Dynamic Risk Assessment for Offender Re-entry (DRAOR; Serin et al., 2012). The DRAOR is a dynamic instrument developed for use by probation and parole officers, to inform case planning and risk management of people under their supervision. The instrument comprises 19 items, originally divided into 3 subscales: stable dynamic risk factors, acute dynamic risk factors, and protective factors. Items were derived and theoretically organized into these subscales based on a review of the literature on violent offender risk assessment and on desistance. Each item is rated using a three-point scoring format (0, 1, 2). A score of ‘0’ indicates the absence of the item, a ‘1’ rating is used to indicate it is somewhat present, or the evidence is inconsistent, and a ‘2’ indicates the item is strongly present.

We conducted a principal components analysis of the items using the initial scores for a medium-sized sample of high-risk offenders (*n* = 299) just released onto parole, including some from this project (Yesberg & Polaschek, 2015a). A model containing four components rather than the original three-subscale structure was a better fit for these data. The Protective subscale was identical in the new structure but the majority of the acute risk factors split to form two subscales (Internal and External Acute). One original acute item loaded on the Stable subscale and one original Stable item loaded on the new External Acute subscale. The empirically derived four-subscale DRAOR is presented in Figure 1 below and was used in this study. DRAOR total scores were calculated—as is the convention— by summing the stable and acute risk items and subtracting the protective items. Total scores range from -12 to 26; higher scores indicate greater recidivism risk.

Insert Figure 1 about here

In New Zealand, all offenders released from prison onto parole are scored on the DRAOR multiple times during their sentence. Supervising probation officers score the DRAOR during every reporting session or non-trivial contact they have with the offender. Depending on an offender’s initial risk level and how long he has been on parole, the DRAOR may be administered twice weekly to biweekly, or at longer intervals. To score the DRAOR, probation officers use information gathered from interviews with offenders, their families or partners, treatment providers, and other external sources (e.g., police intelligence activity, other routine file records). New Zealand was the first jurisdiction to implement the DRAOR across all community supervision and parole offenders, in 2009; DRAOR scores have been found to be predict recidivism in high-risk male offenders (Yesberg & Polaschek, 2015b), women (Yesberg, Scanlan, Polaschek, Hanby, & Serin, 2015), and youth (Fortune, Ferguson, Serin, & Hanby, 2015). Most offenders’ scores are completed by a single probation officer over the whole parole period; however, some may be scored by multiple probation officers because of changes in staffing or location. At the time of writing, the DRAOR’s inter-rater reliability has not been investigated.

Demographic, criminal history, and recidivism data. Research assistants extracted these data from Department of Corrections electronic records. Static risk estimation of the likelihood of future imprisonments was made using the RoC*RoI. The RoC*RoI (Bakker Riley, & O’Malley, 1999) is the New Zealand Department of Corrections’ tool for actuarial risk assessment, developed and cross-validated on two samples, each of 24,000 offenders. Expressed as a probability between 0 and 1, it is an offender's estimated risk of reconviction leading to re-imprisonment over the following five years. The RoC*RoI score is generated by computer algorithm, based largely on criminal history variables, and represents a static estimate of serious reconviction risk. It requires no clinical judgment or manual decision-making, and can be updated at any time, although it changes very slowly, and not at all in response to in-prison behavior. During development, the RoC*RoI demonstrated high predictive validity—an AUC of 0.76 (Bakker, O'Malley, & Riley, 1998)—and later analyses confirm its predictive validity over three years following release (Nadesu, 2007). Other demographic information was extracted from offenders' files.

Procedure

Treatment sample. HRSTU treated men were selected from among those who completed one of the HRSTU programs and were subsequently paroled between 2010 and 2013[5]. Once the New Zealand Parole Board had made a decision about each treated prisoner's release date, members of the research team approached as many as possible of the eligible men, inviting them to take part in our research (known as the 'Parole Project'). Forty-two of those approached by prison staff or members of the research team declined to take part in the research; these men did not differ significantly from those who participated (n = 151) on any demographic or offence history variable.

Comparison sample. The comparison sample of 153 men was recruited from prisoners known not to have completed HRSTU treatment during their current sentence, but who met criteria for referral. As for the treatment sample, project staff monitored the allocation of release dates for potentially eligible offenders, and approached them to take part in the research one to

[5] Because the aims of the overall project were to compare HRSTU completers with eligible men who did not attend, treatment non-completers were not included in this study. However, we have reported on their outcomes previously for one of these units {Polaschek, 2011 #4465}.

five weeks prior to release. Fifty-four comparison men declined to participate when approached; they were statistically indistinguishable from those who took part with one exception. More Māori and Pasifika men and fewer NZ European men declined to take part in the research compared to those who consented.

Once released, the men commenced reporting regularly to the Community Probation Service, according to the conditions of the parole license. Each man's supervising probation officer used the DRAOR to score his current risk and protective factors. DRAOR data were extracted by the research team no less than 12 months after release, and collated for analysis.

Insert Table 1 about here

Data Analyses

All analyses were conducted using SPSS version 22. In the first part of the results, we used independent samples t-tests to test the hypotheses that treatment completers would have significantly lower scores on acute and stable dynamic risk factors, higher scores on protective factors at release, and less variability in these scores over time. Throughout these analyses, and consistent with renewed calls to move away from an overreliance on null hypothesis significance testing (e.g., Cumming, 2012), we present the results as t-tests with effect sizes and confidence intervals and interpret them with reference to both traditions. We also use Pearson's correlations to explore whether variability in acute risk is related to initial levels of stable and protective factors.

We used the Hanson et al. (2007) method to investigate variability differences in dynamic risk and protective factors over the first two months after release: a period we were particularly interested in because of the difficulties many high-risk offenders encounter in these first few weeks. Variability was examined using the standard deviation of scores over time for each individual offender. A mean standard deviation was calculated for each man's DRAOR scores within the first two months of release (see Table 3). In the present analyses, a small standard deviation would indicate that there is little variation in DRAOR scores across time for an offender. A large standard deviation on the other hand would indicate that there is much more variation within the data.

In the remainder of the analyses, we used multilevel growth modelling (MLM) to explore patterns of change in DRAOR scores after release (Field, 2013). MLM is usually applied to data where multiple individuals are nested within a group (e.g., students within classrooms), but the model can also be applied to repeated measurements nested within individuals (Curran, Obeidat, & Losardo, 2010). In other words, MLM allows for the estimation of inter-individual variability in intra-individual patterns of change over time. Unconditional linear growth models provide an understanding of within-person growth trends (e.g., an individual’s initial score and how much it changes over time). Conditional growth models, on the other hand, can be used to evaluate hypotheses about between-person differences in growth trends. In the current study, for example, we test whether treatment status explains difference in growth trends of DRAOR scores.

The benefits of using multilevel modelling (MLM) over traditional repeated measures analysis of variance include MLM’s ability to handle missing data, and provide readily interpretable results regarding rates of change over multiple measurement occasions (Yang et al., 2015). The number of measurement occasions and even the measurement intervals can vary between individuals. Here growth curve modeling is ideal because we wanted to compare starting points and rates of growth by whether or not men had taken part in intensive treatment (or been released early on parole) over as many as 12 measurement occasions scored at different intervals. The steps and analyses will be described below.

Results

We have previously established that the two samples are sufficiently closely matched on static variables to support the attribution of post-treatment differences to the effects of treatment

(Polaschek, et al., 2015). We found that the only significant difference was that treatment men were serving longer sentences (*d* = .30) [6].

Dynamic Risk and Protective Factors After Release

Independent samples *t*-tests were conducted to examine whether there were differences in initial DRAOR scores between the treatment and the comparison samples. Means, standard deviations, and *t*-values are presented in Table 2 for the individual DRAOR item and subscale total scores, along with effect sizes and confidence intervals. Immediately after release treatment men had significantly lower stable subscale scores, significantly lower internal and external acute subscale scores, significantly higher protective subscale scores, and significantly lower total DRAOR scores. Scores for individual items were significantly different for most items with the exception of “peer associations”, “anger/hostility”, “negative mood”, and “interpersonal relationships”. The strongest effect sizes (medium to large) were for the stable item “employment” and the protective items “responsiveness to advice” and “costs/benefits”, and for the stable and protective subscale total scores and the DRAOR total score. Most effect sizes were small to medium, according to Cohen’s criteria (1988)[7], with relatively wide confidence intervals. All differences were in the expected directions.

Insert Table 2 about here

Variability in Dynamic Risk and Protective Factors During Re-entry

As we noted above, the next analyses replicate the Hanson et al. (2007) method to investigate variability differences in dynamic risk and protective factors over the first two months after release. Offenders were excluded from these analyses if they had fewer than three

[6]The combined differences between these two samples on all of the collated demographic and criminal history items were too small to justify their use as a statistical control for sample equivalence (i.e., a propensity analysis). Together they yielded a pseudo-R^2 of less than 6% and a non-significant model when entered into a logistic regression to predict sample membership. Hence no such correction was made (Polaschek et al., 2015).

[7] Cohen’s *d* can be interpreted as 0.2 to 0.3 = small effect, around 0.5 = medium, and greater than 0.8 = large.

ratings in the two months following release because three was the minimum requirement for modelling multiple time-point data; 1 treatment completer and 7 comparisons were excluded. The average number of DRAOR scores for the remaining 296 offenders in the first 2 months was 9.03 (*SD*=3.05, range 3-20): about one assessment per week.

As shown in Table 3 and Figure 2: for the treatment sample, standard deviations were largest for the stable item "employment" and internal acute items. For the comparison sample, standard deviations were largest for the stable item "peer associations", all internal acute items and the external acute item "living situation". Independent samples *t*-tests were used to statistically compare differences in variability across the two groups. Treatment completers had significantly less variability in their ratings (as evidenced by significantly lower standard deviations) for the stable items "entitlement" and "opportunity/access to victims", and for the acute items "substance abuse", "negative mood", "living situation", and "attachment with others", compared to the comparison sample. Treatment completers also had significantly less variability in their internal and external acute total ratings. Effect sizes suggest a small to medium effect for all significant results. There were no significant differences in variability for most of the stable items, all of the protective items, and the stable and protective subscale totals.[8]

Insert Table 3 about here

Insert Figure 2 about here

Taken together, these results suggest that consistent with our hypotheses, the acute items showed the most variability over time. In particular, all three internal acute items and the external acute item "living situation" were the most variable. The external acute items "interpersonal relationships" and "attachment with others" on the other hand had similar

[8] The analyses were repeated excluding 12 treated and 36 comparison offenders who were convicted of a new offence committed within the 2-month time period, to see whether there are still differences after taking into account the greater number of "fast failures" in the comparison sample. The results were markedly similar. All significant differences were found again with this sub-sample with the exception of the internal acute item "negative mood" and the internal acute total score.

standard deviations to the stable items. Of note, the stable item “employment”, which was an acute item in the original DRAOR structure, was also found to have one of the largest standard deviations. But the differences in variability between the treated and comparison offenders were found mostly in the acute items, suggesting that treatment completers were showing more stability in their acute risk factors than the comparison sample during re-entry; variability in the stable/protective items was comparable for both groups.

Finally, we correlated participants’ initial DRAOR scores with their mean standard deviations. We were especially interested in whether acute variability for the first two months after release was related to initial stable risk and protective scores, as dynamic risk theory might suggest. Table 4 shows the pattern of correlations across the combined samples. Several trends can be detected. First, as we might expect given the relative stability of stable and protective factors, associations between all types of initial scores and stable and protective variability were generally small to negligible. Second, internal acute variability showed the most consistent associations with initial DRAOR scores and in the expected direction (i.e., positive for all subscales except initial protective scores). External acute variability also showed several significant correlations with initial DRAOR scores, but these were small in magnitude.

Insert Table 4 about here

Patterns of Change Over Time: Multilevel Modelling

Next, multilevel growth modelling was used to examine whether treatment completers and comparisons differed in their rates of change over a longer period of time than in the previous analyses (2 months). Average monthly DRAOR scores were calculated for each offender for up to 12 months following release. In order to be included in the analysis, offenders were required to have a minimum of three months of DRAOR data. The “fast failures”—men who were reconvicted for offending within two months of release—were excluded from these analyses in order to examine change only for those offenders who remained in the community past this very early period of re-entry. Any DRAOR ratings following the offence date for the first reconviction (excluding breaches of parole) were excluded from the analysis. Of the 304 in the combined sample, 237 had at least three months worth of DRAOR data available (i.e., 135 treatment and 102 comparison men). But samples sizes reduced over time, due to parole ending or reconviction: At 6 months there were 96 treatment and 69 comparison men; by 12 months these figures were 19 and 10 respectively.

Because average monthly DRAOR scores were used as the outcome variable there were no missing data to impute (i.e., every offender had at least one DRAOR score for each month he remained in the study). Further, the scores were thus identically spaced for all offenders, so the time variable was re-coded 0 (month one) to 11 (month twelve). Centering time in this manner allows the intercept to be interpreted as the estimated initial score (i.e., the expected value of the outcome variable when time = 0; Peugh & Enders, 2005).

Unconditional Linear Growth Model. In linear growth models, measurements over time (e.g., monthly average DRAOR scores) are the Level 1 data, nested within individuals (e.g., individual offenders), who constitute Level 2 data. By definition then, Level 1 variables typically vary while being nested under the same Level 2 variable (Hayes, 2006). In other words, Level 2 data provide estimates of the mean intercept (i.e., an individual's starting DRAOR score; often called fixed components) and mean slope (i.e., that individual's rate of change on the DRAOR). Level 1 data provide estimates of the between-person variability in individual DRAOR intercepts and slopes (often called random components). Smaller random effects imply that individuals' intercepts and slopes are relatively similar to each other; larger random effects imply greater individual differences.

Four linear growth models were created using each of the four DRAOR subscales as outcome variables. The equation for each growth model is:

$$\text{Level 1: } Y_{ij} = \pi_{0j} + \pi_{1j}(TIME_{ij}) + r_{ij}$$

$$\text{Level 2: } \pi_{0j} = \beta_{00} + u_{0i}$$

$$\text{Level 2: } \pi_{1j} = \beta_{10} + u_{1i}$$

where Y_{ij} is offender *i*'s score on occasion *j* (i.e., an offender's DRAOR score at each month of follow-up), as a function of the intercept (i.e., initial DRAOR scores, π_{0j}), the slope (i.e., the change in DRAOR scores over time, π_{1j}), and a time-specific residual term (r_{ij}) that captures the portion of offender *i*'s outcome not predicted on occasion *j*. The Level 2 equations describe the individual intercepts (π_{0j}) and slopes (π_{1j}) as a function of the mean intercept (β_{00}) or the mean slope (β_{10}) and an individual deviation from this mean (u_{0i}, u_{1i}). A combined model is obtained by substituting the Level 2 equations into the Level 1 equation:

$$\text{Combined: } Y_{\text{ij}} = \beta_{00} + \beta_{10}(TIME_{\text{ij}}) + \text{u}_{0\text{i}} + \text{u}_{1\text{i}}(TIME_{\text{ij}}) + r_{\text{ij}}$$

The Individual Subscales. Table 5 (Model 1) shows that the average (i.e., all offenders, combining the two groups) stable risk score in the first month following release was 8.45, decreasing an average of 0.13 points per month. The variance of the random components of the intercept was significant, var(u_{0j}) = 6.14, $\chi^2(1) = 495.87$, p<.001, as was the variance of the slopes, var($\text{u}_{1\text{i}}$) = .14, , $\chi^2(1) = 1555.35$, p<.001. These results suggest that there is significant inter-individual variability in offenders' initial scores and rate of change across time. The significant negative covariance (-.18) between the random slopes and intercepts indicate that offenders with higher initial stable risk scores experience lower rates of growth.

The overall pattern is the same for each of the acute subscales[9] and for the protective subscale (Table 6 Model 1) except that for the latter, the significant negative covariance (-.18) was unexpected, and indicates that offenders with a higher protective factor score experience *lower* rates of change.

Insert Table 5 about here

[9] For the internal acute subscale, intercept $\chi^2(1) = 729.91$, p<.001; slope $\chi^2(1) = 250.87$, p<.001. For the external acute subscale, intercept $\chi^2(1) = 1169.95$, p<.001; slope χ^2 (1) = 285.27, p<.001. For the protective subscale, intercept χ^2 (1) = 1614.23, p<.001; slope χ^2 (1) = 578.77, p<.001.

Conditional Linear Growth Model. Because the unconditional growth model analyses for all subscales indicated that offenders differed significantly in their initial scores *and* growth rates, treatment status was added to the models as a Level 2 covariate for both the slope and intercept. The formula for the conditional growth model is presented below:

$$\text{Level 1: } Y_{ij} = \pi_{0j} + \pi_{1j}(TIME_{ij}) + r_{ij}$$

$$\text{Level 2: } \pi_{0j} = \beta_{00} + \beta_{01}(COV_i) + u_{0i}$$

$$\text{Level 2: } \pi_{1j} = \beta_{10} + \beta_{11}(COV_i) + u_{0i}$$

$$\text{Combined: } Y_{ij} = \beta_{00} + \beta_{01}(COV_i) + \beta_{10}(TIME_{ij}) + \beta_{11}(COV_i{*}\ TIME_{ij}) + \mathrm{u}_{0\mathrm{i}} + \mathrm{u}_{1\mathrm{i}}(TIME_{ij}) + \mathrm{r}_{\mathrm{ij}}$$

See Table 5 (Model 2) for the parameter estimates for each subscale. Because all four models revealed the same pattern of results, they are discussed here together. The regression of the intercepts on treatment status was significant for all subscales, suggesting that treatment completers had significantly lower initial stable risk, internal acute risk, and external acute risk scores, and significantly higher initial protective factor scores. The cross-level interaction term (Time*Treatment Status) was not significant for any model, which suggests that treated offenders were no different in their rate of change over time than the comparison offenders, on any of the subscales. The intercept variances declined from the unconditional growth model but were still significant; the slope variances remained unchanged. These results indicate that there is still significant variance unexplained by treatment status, suggesting the need for additional Level 2 covariates.

Using data from the same project, we have recently demonstrated that parole status—whether prisoners were released before or at the end of their sentence—uniquely predicted reconviction, even after treatment status was controlled (Polaschek et al., 2015). This finding suggests that adding parole status (early vs. end-of-sentence) into the models as an additional Level 2 predictor might help reduce some of the unexplained variance. Model 3 in Table 6 shows the parameter estimates for the models with parole status added as an additional Level-2 predictor. Again, the models for all four subscales revealed the same pattern of results and will be discussed together.

When parole status was added into the models as a Level 2 covariate, the regression of the intercepts on treatment status was no longer significant. In other words, treatment status no longer predicted initial average DRAOR scores. But the regression of the intercepts on parole status was significant, suggesting that offenders who were released on early parole had significantly lower average stable, internal acute, and external acute risk and significantly higher average protective scores in the first month following release. The cross-level interaction term for parole status (Time*Parole Status) was not significant, suggesting that early-released parolees were no different in their rate of change over time than offenders released at the end of their sentence. Significant intercept and slope variances indicate that significant variance remains unexplained by treatment status and parole status.

Discussion

Comparing Treatment and Comparison Samples

As expected, the treatment sample entered the community with lower stable and acute dynamic risk scores and higher protective factors than comparison men, and experienced less variability in acute factors. Notwithstanding these more positive initial scores, treated men improved on DRAOR subscales at a comparable rate to the comparison sample. We also found as expected that overall those with higher stable and lower protective factors tended to experience more fluctuations in internal acute risk factors but not in external acute factors, in the early phases of parole. And finally, treatment status was no longer a significant predictor when we introduced early vs. end-of-sentence parole status to examine changes in DRAOR scores. Men with earlier parole, like treated men, had better initial DRAOR scores but changed at the same rate as those released at sentence end. We now discuss each of these findings in turn.

We first examined initial DRAOR scores to explore differences between the two samples in the supervising probation officer's baseline assessment following prisoners' release into the community. Consistent with our first hypothesis, intensively treated high-risk prisoners entered the community with significantly lower stable and acute risk factors and significantly higher protective factors. These results parallel Violence Risk Scale scores just prior to release, which were previously found to be significantly lower in the treatment sample (Polaschek et al., 2015). Almost all differences on individual DRAOR items were statistically significant between the treatment and comparison groups, and most were small to medium effect sizes. However, the two groups were close to equivalent on the stable factor "peer associations", on the acute factors of "anger/hostility" and "negative mood", and "interpersonal relationships". Furthermore, for both groups, peer associations and employment remained significant problems.

Some of the largest group differences were seen in protective factors, in contrast to the assertions made by some critics that RNR-oriented treatment programs such as those provided at these HRSTUs are unlikely to support the development of protective factors (Ward & Brown, 2004). However, we note that our previous validation study of the DRAOR with this sample showed that the protective subscale correlated 0.5 with the stable subscale (Yesberg & Polaschek, 2015a), and a number of items are conceptually similar, for example, to dynamic risk factor items in the VRS. Therefore, although we are confident that developing protective factors is the only plausible conceptual and practical route to ameliorating dynamic risk factors in treatment (Polaschek, 2016), we remain cautious about interpreting these results for the DRAOR protective subscale as providing substantial support for that assertion.

Overall, lower scores on the DRAOR for treated men comprised a large effect size of around 3 rating points. Although these differences might be thought to be due to probation officer expectations about HRSTU treatment completers, in reality, our interviews with probation officers at 2 months following the parolee's release revealed that they usually were unaware of his prison treatment status; an operational oversight that is now being corrected, but that mitigates against simple expectation effects.

Variability in Acute Risk Factors

Following from the first hypothesis, the second was that intensively treated men would show less variability in acute factors. We found that during the first two months back in the community, there was no difference in the amount of variability between samples on most stable or any protective factors. Overall, treated offenders' acute risk factors were less variable in the first two months, consistent with the idea that better (lower) stable and (higher) protective factors may buffer offenders from the chronic coping challenges imposed by repeated fluctuations in acute risk factors. This finding supports the theoretical suggestion we made earlier that treatment may protect against recidivism through reducing the frequency of acute destabilizing events that, according to Zamble and Quinsey's (1997) coping-relapse theory, lead to a higher risk of recidivism. However in this preliminary study we cannot determine the mechanism(s) that may produce this result. Our recent research shows that treatment completion is associated with better release plans, and that planning leads to better two-month release circumstances (Gwynne, Fletcher, & Polaschek, 2015). But an alternative is that completers have more enduring or successful coping responses to initial threats to stability, and so are less likely to exacerbate crises with maladaptive coping (Zamble & Quinsey).

For both samples, acute risk factors also tended to fluctuate more than protective and stable risk factors, although the confidence intervals generally overlapped. This pattern supports the stable/acute distinction postulated by both Beech and Ward (2004) and Zamble and Quinsey (1997). An examination of the correlations between stable and acute factors showed that those with poorer initial scores—subscales and total DRAOR— experienced more internal acute fluctuations, which is also consistent with dynamic risk theory. But the same pattern was not generally seen in external acute variability, suggesting that the latter may be determined by other factors, such as environmental circumstances beyond the offender's control.

Overall Rates of Change

The next section of the analyses simply described the pattern of change over the first 12 months after release. Table 5 shows that as time went on, both the intensively treated and comparison offenders tended to show improvements on all categories of factors. However, what is also evident in these results is the steadily reducing sample sizes, reflecting a mix of reconviction and attrition as parole sentences ended. For example, the comparison sample halved in size between months 6 and 7, because two-thirds of comparison men were on only 6 months of parole after release, whereas treated men were more likely to have longer than 6 months of oversight. Furthermore, as we have shown elsewhere, treatment men were significantly less likely to be reconvicted and returned to prison in their first year, leaving more in the community to continue reporting to the Community Probation Service, and to have their DRAOR scores re-assessed (Polaschek et al., 2015). Of note, external acute factors always remained higher than internal acute factors; a difference that would be worthwhile investigating further. Possibilities for this difference include that probation officers can detect changes in external factors more readily, or have better evidence for them, or monitor them more vigilantly.

Next we turned to growth curve modeling to examine relationships between initial DRAOR subscale scores and rates of change. For Stable, Internal Acute, and External Acute subscales, the pattern was that poorer initial scores were associated with lower growth rates. The one unexpected result was the pattern of change on protective factors; those with stronger initial Protective scores at release changed the least on these same factors. Again, further investigation would be needed to determine why, but discussion with probation practice leaders suggests that perhaps it resulted from a lack of attention by probation officers to further developing the protective factors of parolees who already appeared to be doing well in this domain.

Previously we have shown with this and other DRAOR datasets (e.g., Yesberg & Polaschek, 2015b; Scanlan, Fortune, & Polaschek, 2015) that both stable and protective factors can change substantially over time, and that such changes can be linked to recidivism. Such findings are in contrast to those of Hanson et al. (2007) who found almost no significant change on stable factors, and concluded that they need only be measured perhaps annually. However, this study did not link change to recidivism. Instead we used growth curve modeling to investigate rates of change over time in those who had completed intensive psychological treatment in prison. If this pattern of results does predict recidivism, it may indicate that the frequency of monitoring of stable factors may depend on the nature of the factors themselves (i.e., differences in the tool), or the overall level of dynamic risk, which is likely to be much higher in this study than in the Hanson sample.

The growth models confirmed that the significantly better risk status of treatment sample men on release carried on through time; treatment was associated with higher protective factors and lower stable and acute risk factors for up to 12 months later. Although our analyses do not directly map changes made in treatment onto those made afterwards, they do support the view that offenders not only generalized their progress to the community, but also continued to build on it.

However, their rate of change was similar to that of the comparison men, providing no evidence for the idea that treatment might lead to an accelerated rate of change in the community. Furthermore, parallel rates of change for treatment and comparison samples means that we should not necessarily attribute to treatment the continued improvement in the community. It may instead indicate that community supervision is itself an effective intervention, or even represent regression to the mean. We had no access in this study to information about how probation officers made use of the DRAOR scoring (e.g., whether scores or score changes led them to apply specific interventions to offenders' problems), but because we interviewed the probation officers, we note anecdotally that they were much more likely to intervene when scores were poorer. In an environment where resources are always constrained, staff will tend to spend less time with offenders whose lives are going relatively smoothly, if others on their caseload are struggling. If this speculation is correct, then an intriguing possibility for future research is that treatment men may have continued to change "under their own steam" while comparison men changed with more assistance from Probation Officers. Examination of parole notes in future research could help to test out this idea. However, as we noted earlier, a number of studies have found that parole itself, when it contains elements of "what works" can be an effective intervention (see also Wan, Poynton, Doorn, & Weatherburn, 2014).

Finally, because adding treatment status to the growth curve models left significant unexplained variance, we decided to add a second Level-2 covariate: parole status (i.e., whether men were released onto parole oversight before or at the end of their prison sentence). This variable is strongly correlated with HRSTU treatment. This association is to be expected; the national parole board indicates to many high-risk men that their only viable option for early release is successful completion of an intensive rehabilitation program. So it is unsurprising that while 80% of treatment completers were released early, only one-third of the comparison sample were given early release. When we added the type of parole release granted to participants to the growth curve models, it was a significant predictor of initial scores, and sample membership (treatment vs. comparison) became non-significant. This pattern suggests that parole status is a better predictor than sample status of DRAOR scores in the community, a result that fits with other research with this sample (e.g., Polaschek, Yesberg, & Chauhan, 2016), and suggests that the parole board is relatively effective in identifying those with better release prospects. However, it does not invalidate the importance of HRSTU treatment; it simply indicates that there are other effective approaches to gaining early parole. We recently demonstrated that parole status uniquely predicted reconviction, even after treatment status, dynamic risk prior to release, and quality of release plans were controlled (Polaschek et al., 2015). However, in the current study, parole status, like treatment status, did not predict growth on any DRAOR subscale over time. Rate of growth was equivalent for all subscales, for those released early and those who stayed for their full sentence. And the significant unexplained variance suggests that there are still key variables other than treatment and parole status that could help to better account for the DRAOR findings.

Conclusions and Limitations

This study set out to examine dynamic risk factors in the community and their patterns of change, in part to shed light on how differences associated with treatment completion may carry over into the community: an area that is rarely studied. We demonstrated that intensive treatment completers, and indeed all of those granted early release by the parole board entered the community in a better position to avoid recidivism because of lower stable and acute risks and better protective factors. However, this study was preliminary in scope and thus had significant limitations. First, we did not link DRAOR scores to recidivism directly, an important next step. Second, we did not independently ascertain whether those who were still in the community in the later time intervals had similar or systemically different DRAOR scores to those who were removed earlier from the follow-up. It is much easier to interpret patterns of change when exactly the same cohort is followed for the same time interval. But that means dropping out the higher risk cases, and here we wanted to maximize sample size and describe patterns of change over as long a period as possible.

Third, a limitation that we plan to address in future research is that this study did not statistically link change during treatment to change after treatment. Although change data were collected using two different measurement instruments—the VRS and the DRAOR—it would still be worth exploring whether those who do best in treatment are also initially lower risk cases on the DRAOR, and whether their rate of change is similar to or greater than those who have higher post-treatment VRS scores, or make less change during treatment. But these questions will require different methodologies to those used here. An intermediate step with growth curve modeling will be to follow the two stage model as suggested by Yang et al. (2015), which would link change scores to recidivism outcomes, with the necessary statistical controls incorporated (e.g., type of parole). Relatedly, while on parole some offenders take part in brief interventions with psychologists, to address alcohol and drug use and so on. We would like to investigate whether the role of participation in these interventions is related to DRAOR scores.

To conclude, we set out to examine patterns of change in the community, following a sample of intensively psychologically treated high-risk men for up to 12 months on parole and a similar comparison sample who had either not completed any effective programs while in prison or had completed less intensive programs. Completers of the intensive program entered the community with higher levels of protective factors and lower stable and acute dynamic factors, and continued to make progress on all of these fronts as parole progressed. They also showed less variability on acute risk factors, both internal and external, suggesting that they suffered fewer periods of more intense destabilization, as would be theorized. Mechanisms were not directly examined in this study, but these findings are broadly consistent with the coping-relapse theory of recidivism proposed by Zamble and Quinsey (1997). However, gains were also made by the comparison sample, suggesting that parole itself may be an effective intervention.

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Table 1
Characteristics of Research Participants in the Treatment and Comparison Samples

Variable	Treatment (*n*=151)	Comparison (*n*=153)			
	Means (SDs)		*t (p)*	*d*	*95% CI (d)*
Age at release	32.8 (8.5)	31.1 (8.6)	1.8 (.07)	.20	[-.03, .42]
RoC*RoI[a]	.74 (.14)	.74 (.09)	-.18 (.85)	.00	[-.22, .22]
No. previous convictions	67.1 (53.3)	69.5 (50.0)	-.40 (.69)	-.05	[-.27, .18]
No. previous violent convictions	4.9 (4.4)	4.8 (4.5)	.18 (.86)	.02	[-.20, .25]
Age first conviction	15.9 (2.1)	16.1 (1.6)	-.92 (.36)	-.11	[-.33, .12]
Age first violent conviction[b]	18.9 (3.8)	18.8 (3.5)	.28 (.78)	.03	[-.20, .25]
Sentence length given (days)[c]	1549 (946)	1267 (915)	2.58 (.01)	.30	[.07, .53]
	%		χ^2 (*p*)	Φ/*V*	*95% CI (Φ/Cramer's V)*

Ethnicity			3.1 (.38)	.10	[.06, .21]
Māori	63	67			
NZ European	31	26			
Pasifika	10	8			
Other	0	1			
Index violent offense[b]	70	61	2.2 (.14)	-.09	[-.19, .04]
Released before end of sentence	80	33	69.5 (.001)	-.48	[-.57, -.37]

Notes.[a]RoC*RoI is static measure of risk of imprisonment over next 5 years, expressed as a probability; see below for full description. [b]Almost all participants had a history of violent acts, but a few had no convictions for violence. [c]Excludes 12 treated and 3 comparison men who were serving sentences of indeterminate length (e.g., Life).

Table 2
Comparison of Initial DRAOR Scores for Treatment and Comparison Samples

	Treatment	Comparison				
	M (SD)	*M (SD)*	*t*(302)	*p*	*d*	95% CI *(d)*
Stable						
Peer Associations	1.32 (.51)	1.36 (.57)	-0.67	.502	-0.07	[-.30, .15]
Attitudes To Authority	.93 (.60)	1.14 (.63)	-2.87	**.004**	-0.32	[-55, -.11]
Impulse Control	1.23 (.46)	1.42 (.52)	-3.20	**.002**	-0.37	[-.59, -.14]
Problem Solving	1.15 (.48)	1.29 (.52)	-2.46	**.014**	-0.28	[-.50, -.05]
Entitlement	1.11 (.58)	1.31 (.56)	-3.19	**.002**	-0.35	[-.58, -.12]
Opportunity/Access	.95 (.55)	1.15 (.57)	-3.07	**.002**	-0.36	[-.58, -.13]
Employment	1.57 (.64)	1.79 (.47)	-3.45	**.001**	-0.39	[-.62, -.17]
Total	8.27 (2.38)	9.46 (2.35)	-4.40	**<.001**	-0.50	[-.73, -.27]
Internal Acute						
Substance Abuse	.75 (.60)	.92 (.63)	-2.44	**.015**	-0.28	[-.50, -.05]
Anger/Hostility	.45 (.62)	.59 (.66)	-1.87	.062	-0.22	[-.44, .01]
Negative Mood	.41 (.56)	.52 (.59)	-1.61	.108	-0.19	[-.42, .03]
Total	1.61 (1.31)	2.03 (1.38)	-2.70	**.007**	-0.31	[-.54, -.07]

External Acute						
Interpersonal Rel'ps	1.10 (.50)	1.19 (.57)	-1.47	.144	-0.17	[-.39, .06]
Living Situation	.53 (.60)	.76 (.67)	-3.14	**.002**	-0.36	[-.59, -.13]
Attachment with Others	.95 (.50)	1.10 (.51)	-2.61	**.010**	-0.30	[-.52, -.04]
Total	2.58 (1.12)	3.05 (1.27)	-3.43	**.001**	-0.39	[-.62, -.16]
Protective						
Responsive to Advice	1.01 (.40)	.82 (.44)	4.09	**<.001**	0.46	[.23, .69]
Prosocial Identity	.89 (.41)	.73 (.51)	2.92	**.004**	0.34	[.12, .57]
High Expectations	1.12 (.45)	.94 (.48)	3.36	**.001**	0.39	[.16, .61]
Costs/Benefits	1.08 (.47)	.88 (.49)	3.60	**<.001**	0.42	[.19, .64]
Social Support	1.08 (.47)	.95 (.57)	2.10	**.037**	0.25	[.02, .47]
Social Control	.87 (.43)	.71 (.49)	3.08	**.002**	0.35	[.12, .57]
Total	6.05 (1.71)	5.04 (2.15)	4.52	**<.001**	0.52	[.29, .75]
DRAOR Total	6.41 (4.61)	9.50 (5.15)	-5.51	**<.001**	-0.63	[-.86, -.40]

Table 3
Comparison of Mean Standard Deviations for Treatment and Comparison Offenders (first two months on parole)

	Treatment	Comparison				
	Mean SD	Mean SD	*t*(294)	*p*	*d*	95% CI
Stable						
Peer Associations	.10	.18	-0.68	.496	-0.08	[-.31, .15]
Attitudes To Authority	.11	.14	-1.45	.149	-0.17	[-.40, .06]
Impulse Control	.08	.09	-0.68	.497	-0.08	[-.31, .16]
Problem Solving	.08	.10	-0.59	.554	-0.07	[-.30, .03
Entitlement	.06	.11	-2.29	**.023**	-0.27	[-.50, -.04]
Opportunity/Access	.07	.13	-2.58	**.010**	-0.30	[-.53, -.07]
Employment	.21	.15	1.62	.105	-0.19	[-.04, .41]
Total	.58	.63	-0.65	.518	-0.08	[-.30, .15]
Internal Acute						
Substance Abuse	.18	.25	-2.17	**.031**	-0.25	[-.48, -.02]
Anger/Hostility	.19	.23	-1.28	.201	-0.15	[-.38, .08]

Negative Mood	.17	.24	-2.49	**.013**	-0.29	[-.52, -.06]
Total	.46	.57	-2.10	**.037**	-0.24	[-.48, -.02]
External Acute						
Interpersonal Rel'ps	.10	.14	-1.71	.088	-0.20	[-.43, .03]
Living Situation	.16	.24	-2.42	**.016**	-0.28	[-.51, -.05]
Attachment with Others	.05	.10	-2.39	**.017**	-0.28	[-.51, -.05]
Total	.28	.42	-3.08	**.002**	-0.36	[-.59, -.13]
Protective						
Responsive to Advice	.09	.09	-0.22	.824	-0.03	[-.25, .20]
Prosocial Identity	.07	.07	-0.29	.773	-0.03	[-.26, .20]
High Expectations	.10	.11	-0.35	.726	-0.04	[-.27, .19]
Costs/Benefits	.10	.13	-1.33	.184	-0.15	[-.38, .07]
Social Support	.09	.10	-0.71	.476	-0.09	[-.31, .14]
Social Control	.07	.08	-0.55	.580	-0.06	[-.29, .16]
Total	.46	.51	-0.72	.474	-0.08	[-.31, .14]

Table 4

Pearson's Correlations (with p-values) Between Initial DRAOR Scores and Variability Over First Two Months of Parole

	Participants' Mean Standard Deviations			
Initial DRAOR scores	Stable	Protective	Internal Acute	External Acute
Stable	.045 (.442)	-.023 (.694)	**-.219** (<.001)	.076 (.194)
Protective	-.057 (.330)	**-.119** (.040)	**-.153** (.008)	**-.114** (.050)
Internal Acute	.016 (.785)	.014 (.809)	**.406** (<.001)	.056 (.336)
External Acute	.019 (.743)	**.117** (.045)	**.180** (.002)	**.242** (<.001)
Total	.052 (.369)	.068 (.246)	**.314** (<.001)	**.153** (.008)

n=296

Table 5

Parameter Estimates for Linear Growth Models for DRAOR subscales: Growth Curve Models

	Stable			Internal Acute		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Fixed Components						
Intercept	8.45*** (.17)	8.95*** (.25)	9.43***(.28)	1.39*** (.07)	1.65*** (.11)	1.81*** (.13)
Slope	-.13*** (.03)	-.15** (.04)	-.16** (.05)	-.06*** (.02)	-.08** (.02)	-.10** (.03)
Treatment Status		.87** (.33)	-.39 (.34)		-.45** (.14)	-.29 (.16)
Time*Treatment Status		.03 (.06)	.03 (.06)		.05 (.03)	.04 (.04)
Parole Status			-1.16** (.34)			-.40* (.16)
Time*Parole Status			.01 (.06)			.02 (.04)
Random Components						
Intercept	6.14*** (.60)	5.99*** (.58)	5.59*** (.55)	1.11*** (.12)	1.06*** (.11)	1.04*** (.11)
Slope	.14*** (.02)	.14*** (.02)	.14*** (.02)	.04*** (.01)	.04*** (.01)	.04*** (.01)

Covariance	-.18* (.07)	-.18* (.07)	-.18* (.07)	-.11*** (.02)	-.10*** (.02)	-.10*** (.02)
Goodness-of-fit						
Deviance (-2LL)	5577.85	5575.29	5568.34	3936.85	3934.72	3935.36
	External Acute			Protective		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Fixed Components						
Intercept	2.55*** (.08)	2.74*** (.12)	2.91*** (.13)	5.95*** (.14)	5.48*** (.21)	5.08*** (.24)
Slope	-.06*** (.01)	-.08*** (.04)	-.08** (.02)	.13*** (.03)	.13** (.04)	.10* (.05)
Treatment Status		-.33* (.15)	-.16 (.17)		.83** (.28)	.43 (.30)
Time*Treatment Status		.02 (.02)	.01 (.03)		.00 (.05)	-.03 (.06)
Parole Status			-.41* (.17)			.98** (.29)
Time*Parole Status			.02 (.03)			.07 (.06)
Random Components						
Intercept	1.29*** (.13)	1.27*** (.13)	1.23*** (.12)	4.61*** (.45)	4.46*** (.43)	4.26*** (.42)

Slope	.02*** (.00)	.02*** (.00)	.02*** (.00)	.12*** (.01)	.12*** (.01)	.12*** (.01)
Covariance	-.08*** (.02)	-.08*** (.02)	-.08*** (.02)	-.18** (.06)	-.18** (.06)	-.20*** (.06)
Goodness-of-fit						
Deviance (-2LL)	3471.64	3474.67	3475.25	4980.67	4976.25	4963.46

***$p < .001$, **$p < .01$, *$p < .05$

Stable Subscale	Internal Acute Subscale	External Acute Subscale	Protective Subscale
Peer associations	Substance abuse	Interpersonal relationships	Responsive to advice
Attitudes towards authority	Anger/hostility	Living situation	Prosocial identity
Impulse control	Negative mood	Attachment with others	High expectations
Problem-solving			Costs/benefits
Sense of entitlement			Social supports
Opportunity/access to victims			Social control
Employment			

Note. As indicated by the shading, *opportunity/access to victims* and *employment* were theorized to be acute risk factors in Serin's original (2007) DRAOR and *attachment with others* was originally a stable risk factor.

Figure 1. Empirically derived four-subscale DRAOR structure.

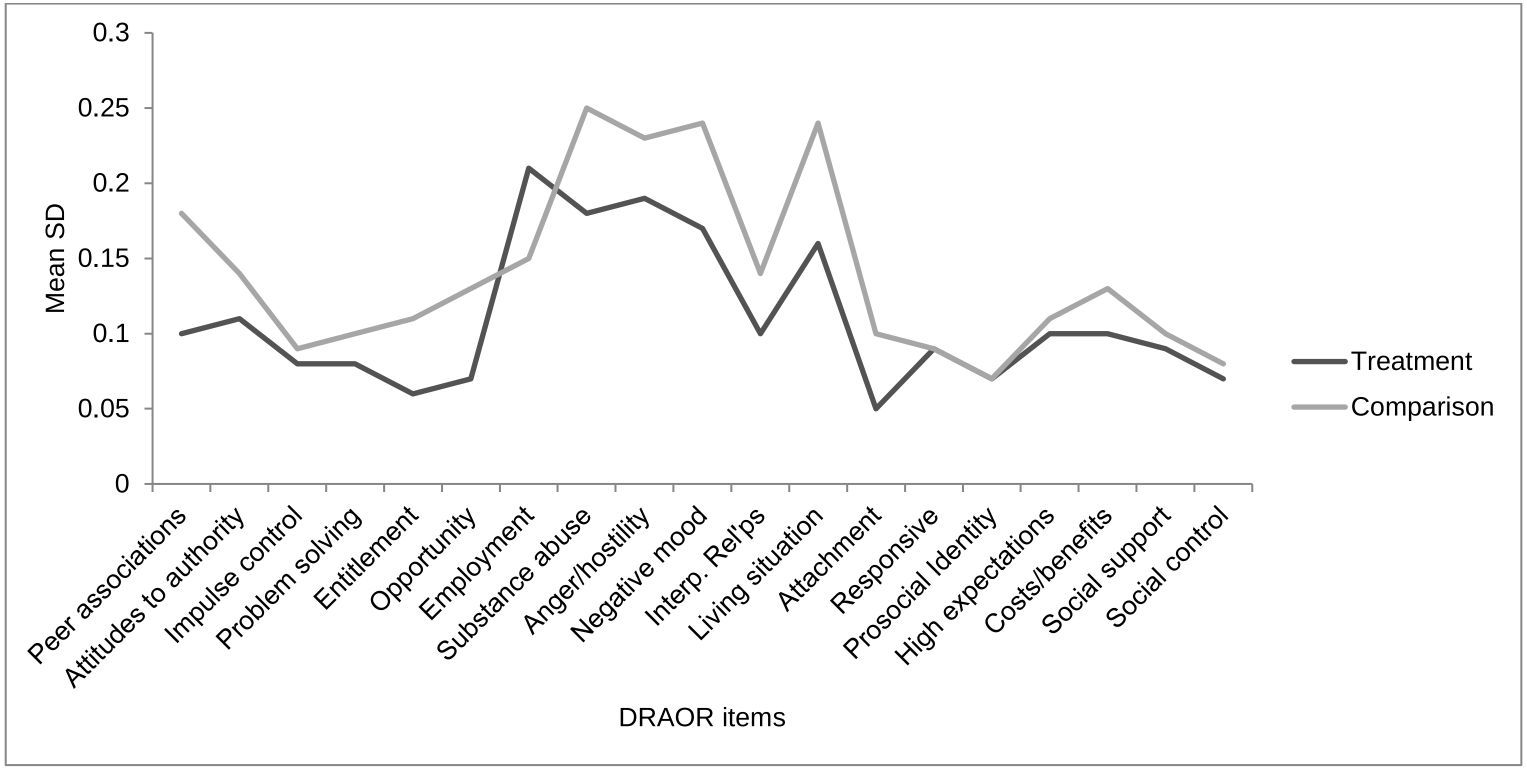

Figure 2. Variability in DRAOR items: Mean standard deviations for ratings made over first two months post-release.