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Sudden gains in day-to-day change:

Revealing nonlinear patterns of individual improvement in depression

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Abstract

Objective: We examined individual overall trajectories of change and the occurrence of sudden gains in daily self-rated problem severity, and the relation of these patterns to treatment response.

Method: Mood disorder patients ($N = 329$, mean age = 44, 55% women) completed daily self-ratings about the severity of their complaints as a standard part of treatment, using the Therapy Process Questionnaire (TPQ). Per individual, the best-fitting defined (linear, log-linear, one-step) trajectory was tested for significance: for change over time, and for specificity of the best-fitting trajectory. 203 cases had ICD-10 Symptom Rating (ISR) depression scores post-treatment: a score ≤ 1 identified 114 treatment responders. Relation to response was examined for sudden gains and type of change trajectory.

Results: 138 cases (42%) had a significant decrease in problem severity, of which 54 cases (16%) had a defined trajectory: 50 cases with one-step improvement, and 4 with a linear improvement in daily problem severity. Sudden gains occurred in 28% of the total sample, and within 58% of improvement patterns. Specifically, sudden gains occurred in 68% of significant one-step trajectories, and 25% of the linear cases. Sudden gains and non-specific change trajectories were significantly more frequent for treatment responders.

Conclusions: At the day-level, patterns of improvement are nonlinear for most patients. Sudden gains occur within various forms of overall change and are associated with treatment response. Clinically relevant improvements in depression occur both gradually and abruptly, and this finding allows for the possibility that the remission process functions according to dynamical systems principles.

Public Health Significance Statement

Mapping individual changes in depressive problem severity with daily measurements during treatment reveals that most mood disorder patients show a non-specific, nonlinear improvement trajectory overall, and clinically relevant jumps (sudden gains) occur as a part of the improvement process for most patients. This study shows that these patterns are related to treatment response, and thereby highlights the clinical relevance of monitoring the pattern of change in individual patients during treatment.

Introduction

The course of depressive symptom change over time has been at the core of many psychotherapy studies aimed at gaining insight into how people get better and whether a particular pattern of improvement is indicative of better long-term outcomes (Aderka, Nickerson, Bøe, & Hofmann, 2012; Howard, Kopta, Krause, & Orlinsky, 1986; Kopta, 2003; Lutz, Martinovich, Howard, & Leon, 2002). Depression research generally holds the assumption that remission and recovery of symptoms is a linear process, based on group-level studies with pre- and post-measurements (Hayes & Hayes, 2007; Laurenceau & Feldman, 2007). This assumed gradual improvement has been challenged by investigations of the therapy process at the individual level, showing that idiographic patterns of change can also be nonlinear (Dunn et al., 2012; Hayes, Laurenceau, Feldman, Strauss, & Cardaciotto, 2007; Rabin, Kaslow, & Rehm, 1984; Uher et al., 2010). A study using weekly symptom assessments revealed that a steady, linear shape of change was only present in about 20% of patients (Vittengl, Clark, Thase, & Jarrett, 2013). Around 30% of people showed a log-linear trajectory of change, with strong improvements at the beginning of therapy, followed by slower, less steep progress thenceforth (Ilardi & Craighead, 1994; Lutz, Stulz, & Köck, 2009; Vittengl et al., 2013).

Another frequently found pattern is a sudden, large, clinically relevant decrease in symptoms in the course of treatment. (Tang & DeRubeis, 1999). Sudden gains have been reported to occur for as many as 23% to 46% of patients in various types of psychological treatment, at various time points in the treatment process (Hayes et al., 2007; Kelly, Roberts, & Ciesla, 2005; Lutz et al., 2013; Tang, DeRubeis, Beberman, & Pham, 2005; Tang, Luborsky, & Andrusyna, 2002). However, even when sudden gains occur, they do not always define the overall trajectory: they have been found within the context of an overall gradual course of change in a few studies (Hayes et al., 2007; Thomas & Persons, 2013; Vittengl,

Clark, Thase, & Jarrett, 2015), and the only study that examined individual shapes of change showed that a trajectory-defining mean-shift in symptoms (i.e., one-step change) was the best fitting model for only 16% of their sample (Vittengl et al., 2013).

Whereas traditional approaches to mental disorders cannot explain this wide variety of change patterns, a dynamical system conceptualisation can explain both the presence of gradual change patterns and the occurrence of abrupt shifts (Gelo & Salvatore, 2016; Schiepek, 2009). From this perspective, mental disorders are conceptualised as a complex system of interacting symptoms, behaviour, cognition and emotions, which is capable of taking on different dynamically stable states (Abel, Hayes, Henley, & Kuyken, 2016; Cramer et al., 2016; Hosenfeld et al., 2015; Schiepek, 2009). While change within and from such dynamically stable states often appears gradual, shifts between two states may be abrupt (Gelo & Salvatore, 2016; Thelen & Smith, 1994). Psychopathology researchers have previously shown that mood systems exhibit generic 'early warning signals' that occur when a relevant change is imminent (Hayes & Strauss, 1998; Scheffer et al., 2009; Schiepek, 2009; Schiepek, Heinzel, Karch, Plöderl, & Strunk, 2016; van de Leemput et al., 2014; Wichers, Groot, Psychosystems, ESM Group, & EWS Group, 2016). Just as a dynamical system becomes less stable after exposure to a large or a repeating stimulus, and is more likely to 'tip over' from one state to another (Cramer et al., 2016; Scheffer, 2009, 2010; Schiepek, Tominschek, & Heinzel, 2014), psychotherapy may be an influence on the mood system that increases a patient's likelihood for change and brings them closer to a sudden transition toward improvement of symptoms (Haken, 1992; Hayes et al., 2007; Schiepek, Heinzel, et al., 2016). Thus, one reason to examine how often sudden gains happen within the overall trajectory of change is that this may provide important clues about whether treatment response in depression can be viewed as a nonlinear, dynamical systems process, in which changes occur both gradually and abruptly.

A second reason to study individual patterns of change during treatment is that they may be associated with later mental health outcome. Patterns of early improvement during treatment have been linked to better long-term outcomes in several studies (Lutz et al., 2009; Rubel et al., 2015; Stulz, Lutz, Leach, Lucock, & Barkham, 2007; Tadić et al., 2010) and defined change trajectories (linear, log-linear or one-step overall patterns) have been found to have a long-term advantage over less orderly change trajectories (Vittengl, Clark, Thase, & Jarrett, 2016). Sudden gains have also generally been found to be indicative of a better degree of improvement (Aderka et al., 2012; Greenfield, Gunthert, & Haaga, 2011). Yet, it remains unclear to what extent the overall trajectory of improvement itself is predictive of outcome (cf. Vittengl et al., 2016), and to what extent sudden gains *within* these trajectories contribute to a stronger degree of person-specific improvement in depressed patients.

In order to differentiate the relative contributions to better outcomes of a sudden gain or the shape of an individual's overall trajectory, we require a more detailed measurement of change during treatment. The way a change pattern looks over time is highly dependent on the measurement frequency (Lutz et al., 2013; Schiepek, Aichhorn, et al., 2016) and the few studies that examined individual change patterns during treatment used weekly assessments. Although sudden gains theoretically occur between adjacent therapy sessions, without a finer-grained study using daily assessments we remain blind to the momentum, magnitude, and stability of the changes in the days between therapy sessions. Therefore, we examine the individual courses of change in perceived problem severity with naturalistic, daily data gathered from a clinical sample with mood disorders during their treatment for depression.

The aims of the current study are: 1) to examine the relative frequency of defined (linear, log-linear and one-step) overall trajectories of improvement in problem severity scores of patients with mood disorders during therapy; 2) to determine how often sudden gains occur within these trajectories; and 3) to examine whether response to therapy relates to

a) a defined trajectory of overall change, b) having a sudden gain, and c) the combination of a specific trajectory of change and a gain.

Method

Sample and procedures

The dataset was derived from four clinics in Austria and Germany between June 2008 and August 2014. Therapists used the internet-based Synergetic Navigation System (SNS) to monitor the therapy process in real-time through a daily questionnaire (Schiepek, Aichhorn, & Strunk, 2012) with the aim to optimize treatment (Schiepek, 2009; Schiepek, Aichhorn, & Schöller, 2018). As a part of care as usual, the sample of 329 patients with an ICD-10 diagnosis of mood disorder (World Health Organization, 1992) filled out questionnaires each evening starting from the first day of treatment. Ethical approval for the application of the SNS for patient monitoring and the usage of the retrieved data was given by the ethical committee of the state of Salzburg, and all patients signed an informed consent confirming that their anonymised data could be used for empirical purposes and scientific publication (Schiepek, Aichhorn, et al., 2016).

Treatment

The intensive daily treatment program in all clinics consisted of multiple integrative components, including individual and group therapy, mostly cognitive behavioural therapy, physiotherapy, psychomotor therapy, psychoeducation, and creative therapy. Most people were at the clinic as inpatients, though some went home in evenings or weekends. Standard duration of treatment was one to three months, with the potential to be extended by one additional month.

Materials

Therapy Process Questionnaire

Patients completed daily ratings on the 47 items of the Therapy Process Questionnaire (TPQ; Schiepek, Aichhorn, & Strunk, 2012). The TPQ is divided into a five-factor structure, of which we focused on factor II: Problem Severity (Schiepek et al., 2012). The Problem Severity factor is comprised of five items on which the current degree of hindrance due to complaints and symptoms is rated by the patient. For example, "*Today I felt helpless and at the mercy of my problems*", and "*Today my problems affected my daily life*", with the response scale ranging from 0 (not at all) to 6 (very much).

ISR-depression scale

Patients completed the ICD-10 Symptom Rating (ISR) at the start and end of therapy to assess the extent to which they suffered from specific symptoms in the past two weeks (Tritt et al., 2008). The depression scale assesses four constructs: 'depressed mood', 'lack of joy', 'lack of energy' and 'low self-esteem', each rated on a five-point Likert scale, ranging from 0 (not applicable) to 4 (extremely applicable). The instrument has good internal validity, is sensitive to change in depression and has shown convergent validity with other instruments (Brandt et al., 2015; Fischer, Tritt, Klapp, & Fliege, 2010, 2011).

Analysis

Pre-processing steps

To examine the period over which most patients received treatment (i.e., between one and three months) any observations after 100 days were dropped. Missing observations were deleted list-wise.

Overall trajectories of change

To determine which theoretical overall change trajectory best typified the pattern of daily problem severity ratings over time for each individual, we modelled the following defined trajectories: a) Linear change – gradual improvement, b) log-linear change – early, fast improvement that levels out with time, c) a one-step change – modelled as a shift in means, d) null-model – no change over time, for comparison (see also Vittengl et al., 2013, 2016). Per individual, problem severity factor scores were regressed on a) a linear function of time (1, 2, 3…, n), b) a log-linear function of time ($\ln(1, 2, 3…, n)$), c) a one-step model of time (time until the largest shift = 1, time after shift = 0), d) no change over time (intercept-only).

To define the point of the 'step' in the one-step model, we used the *e.divisive* function (ecp package; James & Matteson, 2014) to detect the single largest change point for each individual, by specifying $k = 1$. For this, and the sudden gains analysis (next section), the following settings were kept consistent: the *alpha*-argument was set to the default of 1, so that any distributional change contributed to the detection of a relevant change point. The significance level was set to $p < .01$, and the maximum number of random permutations to $R = 4999$. The number of observations between potential change points was set to seven days: *min.size* = 7. This ensures that a change point can only be detected after a period of at least one week, in accordance with previous studies (e.g., Tang & DeRubeis, 1999; Tang et al., 2005).

To identify the best-fitting trajectory per individual (i.e., linear, log-linear, one-step change, and for comparison: a null-model), we used leave-one-out cross-validation (LOOCV) with the caret package (Kuhn, 2008). This method iteratively uses $n − 1$ observations to predict one left-out observation for the specified model shape until it has tested all data points once. The absolute error reflects the difference between the omitted actual observation and the predicted observation over all iterations; the model with the lowest mean absolute error (MAE) describes the data best. Next, to examine how often the model with the lowest MAE represented

significant change over time, we tested the best model against the null-model for all individuals. To further differentiate whether the significant change trajectory over time took a defined (linear, log-linear or one-step) shape, or was less specific, we tested the best model for each person against their second-best trajectory. Specifically, the comparisons consisted of permutation-based one-way tests of independence on the absolute error time series of the different models, paired on time point, using 500,000 Monte Carlo resampling iterations. This permutation-based method accounts for the small sample sizes, outliers and non-normal distributions (coin package; Hothorn, Hornik, van de Wiel, & Zeileis, 2008).

Sudden gains

To formulate decision rules to test whether the largest shift in the distribution of problem severity scores met the criteria of a sudden gain, we used the definition of sudden gains from Tang & DeRubeis (1999): an improvement between two time points that is large in: 1) absolute magnitude, 2) relative magnitude, and 3) magnitude relative to symptom fluctuation.

To pinpoint the moment at which the largest shift in problem severity scores took place, we used the *e.divisive* function again. First, we did not restrict the number of possible change points (k = NULL) and selected only those cases that had at least one significant change point. Second, to keep only the largest shift in the distribution of scores for those cases, the analysis was run again, now specifying maximum one change point with k = 1.

To determine if the absolute magnitude of the identified shift was sufficiently large (criterion 1), we tested whether the difference between the mean of the week before the change point and the mean of the week after the change point was larger than or equal to an absolute value of 0.8. This value reflects the average within-person standard deviation of the problem severity scores of the first two weeks. We adjusted Tang and DeRubeis' (1999) original first

criterion (i.e., 1 *SD* on the Beck Depression Inventory (BDI); Beck, Ward, Mendelson, Mock, & Erbaugh, 1961) as our study used a different measurement instrument with no established clinical cut-off.

The relative magnitude of change (criterion 2) was tested identically to Tang and DeRubeis (1999): by calculating whether there was at least 25% relative difference in means between the seven days before and the seven days after the identified sudden transition.

The magnitude of the shift relative to symptom fluctuation (criterion 3) was tested as part of the change point analysis: the *e.divisive* function bisects the data and detects a point at which the relative difference in distributional characteristics (most prominently the means and variance) between the two sections is largest. This method might be less prone to detecting false positive sudden transitions than the original criteria (see Vittengl, Clark, Thase, & Jarrett, 2015), as *e.divisive* explicitly tests whether the random fluctuations in scores are significantly different between distributions of scores before and after the change point using permutation testing procedures (Cabrieto, Tuerlinckx, Kuppens, Grassmann, & Ceulemans, 2017; James & Matteson, 2014).

Relation to outcome

Response was defined as an absolute low symptom score on the ISR-depression scale of ≤ 1 post-treatment, indicating minimal depressive severity (Brandt et al., 2015). Scores were only available for part of the sample (*n* = 203), and splitting the group on the ≤1 cut-off resulted in 114 responders, and 89 non-responders.

We examined the association between treatment responder status (0 = non-responder, 1 = responder) and the frequency of patterns of overall change and sudden gains using chi-square tests of independence with an α-level of .05. For the overall trajectories, we first examined whether responder status was related to having a defined trajectory of change over

time (significant trajectory = 1, non-specific significant change = 0). Then, depending on the

resulting group sizes, we tested whether responder status was related to a certain trajectory

group, (categorical variable: linear = 1, log-linear = 2, one-step = 3). Finally, the relative

proportion of sudden gains (no gain = 0, gain = 1) in responders and non-responders was

examined.

Results

Descriptives

The sample (N = 329) included 181 females and 148 males, ages between 18 and 69

years old (M = 43.8, SD = 11). All patients had an ICD-10 diagnosis of mood disorder (World

Health Organization, 1992): Bipolar disorder (n = 23); Major depressive disorder (MDD) –

single episode (n = 149); MDD – recurrent (n = 155); MDD – persistent (n = 2). On average,

missing data was low: 3.05% (SD = 3.94). With a minimum of 28 and a maximum of 100 data

points, the mean number of observations was 62.9 (SD = 22.3). Ratings on the problem severity

scale had a mean of 3.03 (SD = 1.14) in the first seven days, and a mean of 2.43 (SD = 1.33)

in the last seven days. The mean ISR score at intake was 2.27 (SD = 1.05), and 1.11 (SD =

0.99) post-treatment.

Frequency of change patterns

Overall trajectories.

The best-fitting model was indicative of significant change over time (fitted better than the

null-model) for 176 cases (53.5%). Of those, 84 individuals (25.5%) had a significant defined

trajectory – linear, log-linear or one-step (i.e., the best model outperformed the second-best).

Examples of individual trajectories of problem severity over time are illustrated in Figure 1.

Focusing specifically on *improvement* during treatment, Table 1 shows results for the 138

(78%) cases with significant decrease in problem severity over time (i.e., had a negative beta-

Table 1

Change pattern frequencies for cases with a significant improvement in problem severity scores over time

		Overall trajectories			Sudden gain		
		n	%	% of total	*n*	%	% of total
Significant change over time		138	100%	53.5%	81	58.7%	24.6%
Defined trajectory over time	Linear	4	2.9%	1.2%	1	0.7%	0.3%
	Log-linear	0	0%	0%	0	0%	0%
	One-step	50	36.2%	15.2%	34	24.6%	10.3%
	Total	54	39.1%	16.4%	35	25.4%	10.6%

Note:

$N = 138$, total sample $N = 329$. Decrease in problem severity: beta-coefficient of the best model was negative. Significant change: the best model fit better than the null-model at $p < .05$. Defined trajectory: the best model fit better than the second-best at $p < .05$

coefficient). Of those cases, 54 (39%) had significant, defined change trajectories over time, which most often took the shape of a one-step pattern (50 cases; 93%), followed by a linear trajectory (4 cases; 7%). Log-linear trajectories never outperformed the second-best model.

Sudden gains.

In the total sample of 329 participants, we identified 189 (57%) cases that met the criterion of a significant shift in the distribution of their problem severity scores relative to symptom fluctuations. The criterion of absolute size of the gain being 0.8 or larger between the week before and after the change point narrowed the sample to 146 cases (44%). Applying the criterion of a relative change of 25% mean difference between the weeks before and after the change point, yielded a final number of 93 (28%) sudden gains, and 41 (12%) sudden losses (i.e., problem severity increased). Results for the full sample ($N = 329$) are reported separately to allow proportions of change patterns to be compared to the broader existing literature, see Table S1 in the Supplementary materials.
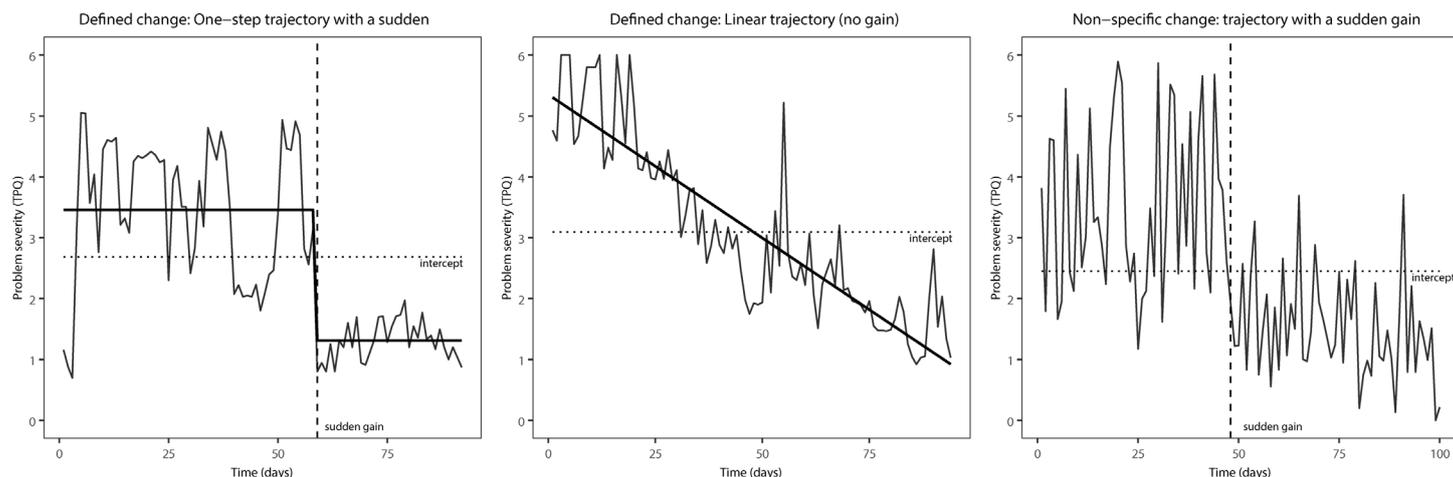
Figure 1.   Three different individual overall trajectories of improvement.
TPQ: Therapy Process Questionnaire. Panel A and B: a defined change trajectory indicates that the best-fitting model fitted significantly better than the second-best model. Panel C: a non-specific change indicates that there was significant change over time (compared to the null-model), but that the best-fitting defined (here: one-step) trajectory could not be distinguished statistically from the second-best alternative (linear, in this case).

Occurrence of sudden gains within significant improvement trajectories.

A sudden gain was identified for 81 (59%) of the 138 cases with significant change toward improvement. In 34 cases (68%) of the defined one-step change group a sudden gain occurred, in the linear group, 1 case (25%) had a sudden gain. Notably, 16 cases had a trajectory-defining one-step shift that did not meet sudden gain criteria.

Associations between patterns of change and treatment response

Non-specific and defined trajectories. To examine whether having a defined trajectory of overall change was related to responder status, we compared the proportions of responders in the group with a significant trajectory of improvement over time ($n = 33$, responder $n = 14$) to the cases that had a significant improvement over time but not a defined trajectory ($n = 52$, responder $n = 41$). We found a significant association between responder status and (un)defined change trajectories, χ^2 (1, $N = 85$) = 4.40, $p = .036$. Specifically, responders were more likely

to have a *non-specific* trajectory, and non-responders more frequently had a defined trajectory, than would be expected by chance.

Specific trajectories. Because the vast majority of cases was categorised as a one-step change, we could not test for associations between the different theoretical change trajectory groups and treatment response.

Sudden gains. Responders ($n = 114$; sudden gain $n = 42$) were found to have significantly more sudden gains relative to non-responders ($n = 89$; sudden gain $n = 17$), χ^2 (1, $N = 203) = 7.63$, $p = .006$. Note: we provide a table of the relative frequencies of the significant change trajectories and sudden gains and losses for the (non-)responder subsample in Supplementary Table S2.

Post hoc: relationship between one-step trajectories and sudden gains

Having found that both sudden gains and undefined change trajectories are related to treatment response, we considered it relevant to examine how often sudden gains shaped the overall trajectory: i.e., do they occur more frequently in one-step improvement? Given the dominance of one-step trajectories in the defined change trajectory group (50 out of 54 cases), we were able to extend our analyses with an additional chi-square test, to compare the proportions of sudden gains in the group with a significant one-step improvement over time ($n = 50$, sudden gain $n = 34$) to the group with non-specific significant change over time ($n = 84$, sudden gain $n = 46$). We found that having defined one-step trajectory was unrelated to having a sudden gain or not: χ^2 (1, $N = 134) = 2.28$, $p = .131$. Thus, sudden gains need not be trajectory-defining, as they occurred equally often in one-step trajectories and other forms of overall improvement, where they were part of a larger gradual or nonlinear change pattern.

Discussion

In this study, we mapped different trajectories of improvement in depressive problem severity at a fine-grained daily level, which adds a new layer of detail to our knowledge of sudden gains and overall change processes in depression. We found that more than half of our sample followed non-specific improvement trajectories, and one-step trajectories were the most common defined trajectory. Our results indicate that responders were more likely to have an undefined shape of overall change, and that sudden gains did not occur more frequently in defined one-step trajectories than in less specific improvement trajectories over time. Moreover, we replicated the finding that sudden gains are a frequent phenomenon and that they are predictive of treatment response.

A defined one-step overall trajectory was clearly most prevalent in our sample. This contrasts findings from studies on week-level individual change, which showed that log-linear shape of change was most prevalent, and one-step trajectories were the least frequent (Hayes & Hayes, 2007; Vittengl et al., 2013, 2016). Group-level studies have most often found linear trajectories in depressive scores during therapy, and our results suggest that this pattern is not applicable to many individuals at a day-to-day level (see also Barkham, Stiles, & Shapiro, 1993; Hayes et al., 2007; Laurenceau & Feldman, 2007). In fact, 61% of patients with a significant improvement could not be categorised by a specific trajectory – this is more than the 34% undefined change that has been found at week-level (Vittengl et al., 2013, 2016). Moreover, undefined trajectories of change were related to being a treatment responder, which is in direct contrast to the finding that *defined* change patterns are related to better treatment outcomes (Vittengl et al., 2016).

It could be that our results contrast those studies because daily measurements capture the fluctuating, dynamic nature of depressive problems and the variability and heterogeneity of therapeutic change over time more closely (Wichers, 2014). The theoretical trajectories of

change employed in this study are derived from studies on weekly data, which typically have fewer observations per person (e.g., 8-20 treatment sessions in various studies on sudden gains, see Aderka et al., 2012), making modelling more complex patterns over time statistically challenging for week-level studies, and possibly of lesser interest. Having more detail over the days creates its own challenge, as we found that the simple theoretical models fit our data less well, resulting in larger errors (Delignières, Fortes, & Ninot, 2004). This may partly explain the relative dominance of the one-step model in the defined group: modelling two means over time allows for more statistical flexibility in finding an optimal fit (and lower errors), than the single line of the linear or log-linear models. The rich, daily data in this study thus shows that the explanatory model of linear improvement during therapy is inadequate for describing patterns of treatment response for most patients in our sample.

Sudden gains occurred frequently within significant improvement trajectories (59% of cases), irrespective of it having a defined one-step change or undefined change. This shows that even when large jumps in symptom reduction occur, they need not define the overall course of change. A previous simulation study already showed that this finding is likely: our study now confirms the occurrence of sudden gains within heterogeneous, gradual overall improvement trajectories with empirical data (Thomas & Persons, 2013). The prevalence of sudden gains, and the individual variation in overall change during therapy can be taken as encouragement to look for new avenues of conceptualising depression and mood systems to account for nonlinearity and individuality.

Although not the only avenue of interest, having found these continuous and discontinuous changes means we should not overlook a complex dynamical systems explanation for understanding patterns of treatment response in depression (Abel et al., 2016; Hayes & Strauss, 1998). Some empirical research has supported the idea that sudden changes in symptoms may be indications of a critical shift in the mood system, where a move toward a

more adaptive state is reached after the positive influence of therapy (Schiepek, 2009; Schiepek et al., 2018, 2017; van de Leemput et al., 2014; Wichers et al., 2016). Examining whether sudden gains in depression indicate tipping points is relevant, as dynamical systems theory may provide us with methods to anticipate changes in symptoms or depressive burden. By looking for the generic signs of imminent change that typify complex dynamical systems (e.g., increases in autocorrelation, variance, dynamic complexity, and connectivity), we may learn to anticipate and protect against changes toward maladaptive states, or encourage positive change when the system is particularly susceptible (Hayes & Strauss, 1998; Hayes, Yasinski, Barnes, & Bockting, 2015; Olthof et al., 2019; Wichers et al., 2016). Clearly, both clinicians and patients would benefit from knowing when and how changes are taking place, and may even adapt the therapy accordingly (Krause & Lutz, 2009; Lutz et al., 2009; Schiepek et al., 2014; Schiepek & Tschacher, 1992). However, these explanations for depressive remission remain tentative for now and require further testing.

Strengths of our study include the high level of detail gained from daily measurements, along with a large sample size and statistically conservative methods throughout – cross-validation and permutation tests were used in assessing overall change trajectory model fit and significance, and in the estimation of the optimal change point. Our analyses also accounted for individual differences in how treatment response in depression develops over time. By focusing on a group of patients who improved over the course of treatment, our findings give a closer description of the day-to-day patterns of improvement in depression. Clinically, this has allowed us to say that if a sudden gain occurs for a patient who keeps taking steps towards improvement – no matter the exact trajectory – their outlook is more promising than for patients who improve without a sudden gain. We chose a different measurement instrument to study the presence of sudden gains (the TPQ rather than the BDI; Beck, Steer, & Carbin, 1988; Schiepek et al., 2012) than the original authors (Tang & DeRubeis, 1999), which allowed us to

get a daily pattern of experienced problem severity that serves as a more direct gauge of functioning and response to therapy than the presence of symptoms alone (Barkham et al., 1993). Furthermore, using change point analysis to automate testing of the third sudden gains criterion (relevant change relative to symptom fluctuation) made our method an objective and conservative way to observe the conditions of this debated criterion (Vittengl et al., 2016).

A limitation of our study is that we were unable to compare specific change trajectory groups among one another on treatment response as the group sizes were too unbalanced to test the differences. We also did not investigate the occurrence of more than one, or cascades of gains (Lutz et al., 2013; Schiepek, 2009). We were also limited by our use of the theoretical change trajectories from the weekly literature, as our results suggest that more complex, individualised models may be needed to capture the dynamic nature of change in depressive complaints in daily data. Finally, due to the observational design of this study, we are unable to identify the processes and determinants that underlie the change patterns we identified.

To conclude, this study examined individual trajectories of improvement during therapy with fine-grained daily ratings, and highlights the importance of looking beyond the existing linear theoretical explanations of how depression changes over time. The presence of gradual and abrupt shifts in problem severity can be taken as a first indication that the process of depressive remission may behave according to the principles of complex dynamical systems, in which nonlinear change is common, and this warrants further investigation. Clinically, this is important, as this study shows that nonlinear, variable patterns of change, including sudden gains, can be expected for many depressed patients during treatment and are associated with treatment response.

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Supplementary materials

Table S1

Frequencies of significant change over time and sudden gains and losses in the full sample

		Change trajectory		Sudden gain		Sudden loss	
		n	%	*n*	%	*n*	%
Significant change over time		176	53.5%	81	24.6%	28	8.5%
Defined trajectory over time	Null-model	3	0.9%	0	0%	0	0%
	Linear	4	1.2%	1	0.3%	0	0%
	Log-linear	0	0%	0	0%	0	0%
	One-step	77	23.4%	34	10.3%	18	5.5%
	Total	84	25.5%	35	10.6%	18	5.5%

Note:

Percentages represent the proportion of the total sample ($N = 329$). Significant change: the best model fitted better than the null-model at $p < .05$. Defined trajectory: the best model fitted better than the second-best at $p < .05$

Table S2

Frequencies of significant change and defined trajectories over time and sudden gains and losses, for the 203 patients that could be defined as responders and non-responders

		Change trajectory						Sudden gain						Sudden loss					
		Overall *n* (%)		responders *n* (%)		non-responders *n* (%)		Overall *n* (%)		responders *n* (%)		non-responders *n* (%)		Overall *n* (%)		responders *n* (%)		non-responders *n* (%)	
Total		203	(100%)	114	(56.2%)	89	(43.8%)	59	(29.1%)	42	(20.7%)	17	(8.4%)	27	(13.3%)	12	(5.9%)	15	(7.4%)
Significant change over time		108	(53.2%)	69	(34%)	39	(19.2%)	54	(26.6%)	38	(18.7%)	16	(7.9%)	18	(8.9%)	6	(3%)	12	(5.9%)
Defined trajectory over time	Null-model	2	(1%)	1	(0.5%)	1	(0.5%)	0	(0%)	0	(0%)	0	(0%)	0	(0%)	0	(0%)	0	(0%)
	Linear	1	(0.5%)	0	(0%)	1	(0.5%)	0	(0%)	0	(0%)	0	(0%)	0	(0%)	0	(0%)	0	(0%)
	Log-linear	0	(0%)	0	(0%)	0	(0%)	0	(0%)	0	(0%)	0	(0%)	0	(0%)	0	(0%)	0	(0%)
	One-step	48	(23.6%)	27	(13.3%)	21	(10.3%)	24	(11.8%)	15	(7.4%)	9	(4.4%)	11	(5.4%)	5	(2.5%)	6	(3%)
Total		51	(25.1%)	28	(13.8%)	23	(11.3%)	24	(11.8%)	15	(7.4%)	9	(4.4%)	11	(5.4%)	5	(2.5%)	6	(3%)

Note:
Response was defined as a score of ≤1 on the ICD-10 Symptom Rating depression scale post-treatment. Percentages represent the proportion of the cases with a post-treatment score ($N = 203$). Significant change: the best model fitted better than the null-model at $p < .05$. Defined trajectory: the best model fitted better than the second-best at $p < .05$