Affect Dynamic Signatures of Psychosis Risk Across Multiple Timescales and Contexts

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Abstract

There is a critical need for identifying time-sensitive and cost-effective markers of psychosis risk early in the illness course. One solution may lie in affect dynamics, or the fluctuations of affect across time, which have been demonstrated to predict transitions in psychopathology. Across three studies, the current research is the first to comprehensively investigate affect dynamics in relation to subthreshold positive symptoms (perceptual aberration and magical ideation) and negative symptoms (social anhedonia) of the psychosis spectrum. Across multiple timescales and contexts, affect dynamics were modeled from inexpensive laboratory paradigms and social media text. Findings provided strong evidence for positive symptoms linked to heightened magnitude and frequency of affective fluctuations in response to emotional materials.

Alternatively, negative symptoms showed modest association with heightened persistence of baseline states. These affect dynamic signatures of psychosis risk provide insight on the distinct developmental pathways to psychosis and could facilitate current risk detection approaches.

Keywords: psychosis, risk detection, affect dynamics, sentiment analysis, networks

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Psychotic disorders, such as schizophrenia, affect approximately 0.4% of the population (Moreno-Küstner, Martín, & Pastor, 2018), yet are a leading contributor to disability and economic burden worldwide (GBD 2019 Diseases and Injuries Collaborators, 2020). A much larger segment of the population—estimates ranging from 7-12% (Linscott & van Os, 2013; Meehl, 1990; Nuevo et al., 2012)—experiences subthreshold psychosis, including maladaptive personality traits and psychotic-like experiences that can be primarily categorized into positive symptoms (e.g., perceptual disturbance and magical thinking) and negative symptoms (i.e., diminution in experiences such as social anhedonia; Kotov et al., 2020; Kwapil & Barrantes-Vidal, 2015). Mounting research suggests that these subthreshold psychotic experiences are not qualitatively distinct from full-blown psychosis. Instead, psychosis is better conceptualized as a severity spectrum that ranges from individual differences to clinical disorders (Kotov et al., 2020; Kwapil & Barrantes-Vidal, 2015; Linscott & van Os, 2013; van Os, Hanssen, Bijl, & Ravelli, 2000).

Individuals with subthreshold experiences of psychosis, such as those with elevated psychosis-related personality traits (also known as schizotypy) and those meeting the criteria for clinical high-risk status, have an elevated risk for more severe forms of psychosis and nonpsychotic psychopathology (Chapman, Chapman, Kwapil, Eckblad, & Zinser, 1994; Fusar-Poli et al., 2013; Kaymaz et al., 2012; Kelleher et al., 2014; Kwapil, 1998; Lenzenweger, 2021). Although the majority of people with subthreshold psychosis do not develop a clinically significant psychotic disorder, individuals along the psychosis severity spectrum share risk factors across biopsychosocial domains (Kwapil & Barrantes-Vidal, 2015; Linscott & van Os, 2013). Additionally, subthreshold psychosis can be distressing, and has been associated with

worse physical health, poor daily functioning, and suicidality (DeVylder & Hilimire, 2015; Kelleher et al., 2014; Nuevo et al., 2012; Phillips & Seidman, 2008). Given the phenotypic and risk factor overlap with clinical psychosis, and the inherent associated impairment and distress, research on people with subthreshold psychosis informs the psychosis spectrum and may provide insight into risk factors for illness progression.

Affective abnormalities emerge as a key indicator of risk, given their central role in the presentation, etiology, and maintenance of psychopathology in general (Kring & Mote, 2016) and psychotic disorders in particular (Horan, Blanchard, Clark, & Green, 2008; Li, Dent, Donberg, & Martin, 2021; Myin-Germeys & van Os, 2007). Importantly, there is a burgeoning body of research showing that beyond mean levels of affect, affect dynamics, or the fluctuations of affect across time, can provide a mechanistic understanding of the risk and resilience for psychopathology (Bringmann et al., 2016; Houben, Van Den Noortgate, & Kuppens, 2015; Trull, Lane, Koval, & Ebner-Priemer, 2015; Wichers, Wigman, & Myin-Germeys, 2015). In particular, recent theorizing about the dynamics of complex systems such as affect has proposed a set of indices that typically precede the critical transition from normality to abnormality (Scheffer et al., 2009, 2012; see Table 1 for a brief overview). In the affect system, the dynamic systems theory posits that a few densely connected positive affect (PA) and negative affect (NA) states can make an individual less able to adapt to various internal and external demands (e.g., a vicious cycle of sadness, guilt, and unhappiness). Over time, these emotional states may become more persistent and unstable until only a slight perturbation (e.g., an unpleasant work meeting) may be enough to precipitate a synchronized shift from typical functioning to a pathological state. Indeed, these theoretically important affect dynamic indices have been linked to a wide range of psychopathological conditions (Houben et al., 2015), most notably, predicting future

transitions in symptom severity (Van De Leemput et al., 2014; Wichers & Groot, 2016; Wichers, Smit, & Snippe, 2020). As such, examining affect dynamics in relation to the spectrum of positive and negative psychosis symptoms may uncover novel affective signatures useful for the prediction of psychosis risk.

Table 1

The Definition and Operationalization of Affect Dynamic Indices

Affect Dynamics	Theoretical Relevance	Statistical Operationalization	Substantive Interpretation
Emodiversity	Low diversity and high connectivity density are structural indicators of resistance to change, reflecting a system that is vulnerable for critical transitions (as opposed to gradual adaptations) (Scheffer et al., 2012). High inertia, variability, and synchrony are features of a system that is slow to recover from minor perturbations (i.e., critical slowing down) when at the vicinity of a critical transition (Scheffer et al., 2009, 2012).	Shannon's entropy (Quoidbach et al., 2014). Shannon's entropy for person $j = -\sum_{i=1}^s p_{ij} \times \ln(p_{ij})$, where s is the total number of emotions experienced and p_{ij} is the proportion of the i th emotion in all instances of s .	Lower emodiversity indicates lower variety and relative abundance of the emotional repertoire.
Density		The mean of all absolute within-person centered auto- and cross-regressive slopes in a multilevel vector autoregressive model, in which an emotion (i.e., positive or negative) at time $_i$ is predicted from its past state at time $_{i-1}$ as well as the past state of the other emotion (i.e., negative or positive; Bringmann et al., 2016).	Greater density indicates greater temporal interdependency, and thus resistance to change, of the emotional network.
Inertia		The within-person centered autoregressive slope in a multilevel model, in which an emotion at time $_i$ is predicted from its past state at time $_{i-1}$ (Kuppens, Allen, & Sheeber, 2010).	Greater autocorrelation indicates greater temporal interdependency, and thus resistance to change, of the emotion.
Variability (Overall)		The standard deviation of a person's emotion across time (Eid & Diener, 1999).	Greater standard deviation indicates greater overall amplitude or range of emotional changes.
Instability (Moment-to-Moment Variability)		Square successive difference (SSD) and acute change (AC; Jahng et al., 2008). For both indices of instability, successive differences (SDs) between time $_i$ and time $_{i-1}$ are first calculated. SSDs are calculated as the squared SDs. The AC at time $_i$ is defined by whether the associated SD exceeds a meaningful cutoff (c), with $AC_i = 1$, if $SD \text{ between time}_i \text{ and time}_{i-1} \geq c$, and $AC_i = 0$, otherwise. A recommended AC cutoff is the 90 th percentile of all instances of SDs (Jahng et al., 2008).	Greater SSD indicates greater amplitude and frequency of emotional changes, while greater AC indicates greater acute increase in emotions.
Synchrony		The correlation between within-person centered positive and negative emotions (Dejonckheere et al., 2018).	Given that positive and negative emotions are typically negatively correlated (Russell & Carroll, 1999), a more negative correlation thus indicates greater synchrony or greater inhibition of opposite-valenced emotions.

Despite ample historical accounts linking psychosis to altered affect dynamics (e.g., affective lability and ambivalence; Bleuler, 1911/1950; Meehl, 1990), few studies to date have empirically tested affect dynamic indices as they relate to the psychosis spectrum. Previous studies have relied on the experience sampling method (ESM) to assess naturally occurring affect. Findings have converged to indicate that positive symptoms are tied to elevated NA variability overall, as well as from one moment to the next (i.e., instability), and, to a lesser extent, elevated instability in PA (Kwapil, Brown, Silvia, Myin-Germeys, & Barrantes-Vidal, 2012; Myin-Germeys, Delespaul, & DeVries, 2000; Nittel et al., 2019, 2018; Oorschot et al., 2013; Westermann et al., 2017). Variability and instability in either PA or NA do not appear to characterize negative symptoms, with the majority of studies failing to find any significant associations (Kwapil et al., 2012; Oorschot et al., 2013; Westermann et al., 2017). Instead, one study found that negative symptoms were related to a stronger pull of affect to baseline (i.e., affective set point) that was characterized by low PA and high NA, suggesting elevated inertia of baseline states and elevated regulatory tendencies to baseline following emotional events (Westermann et al., 2017). Similarly, another study showed that negative symptoms were associated with a lower likelihood of maintaining or increasing PA and a greater likelihood of maintaining or increasing NA (Strauss et al., 2020). Overall, evidence points to positive and negative symptoms conveying the opposite patterns of affect dynamics, with the former related to an increased magnitude and frequency of change whereas the latter related to an increased resistance to change from baseline.

Nevertheless, as previous studies have typically only focused on variability or instability in NA, it is relatively unclear how other affect dynamic indices (e.g., emodiversity, density, and synchrony) relate to symptoms of the psychosis spectrum. Preliminary evidence indicates that

these less studied affect dynamic indices are related to the psychosis spectrum. For example, Strauss and colleagues (2020) found greater density of connections between PA and NA, particularly an inhibition of NA on PA, for individuals with schizophrenia than controls. Kimhy and colleagues (2014) showed that compared to controls, individuals with schizophrenia had lower differentiation in discrete emotional states generally (e.g., all states are labelled as “good” or “bad”, rather than “happy”, “sad”, “angry” etc.), but not for negatively-valenced discrete states specifically, possibly pointing to a reduced overall, but not negative, emodiversity. However, little is known regarding whether emodiversity, density, and synchrony could differentially relate to positive and negative symptoms of the psychosis spectrum as do other affective dynamic indices. At the same time, a comprehensive examination of affect dynamics is needed, in light of findings showing that a combination of different indices enhanced the predictive sensitivity and specificity for depressive symptom transition (Van De Leemput et al., 2014; Wichers & Groot, 2016; Wichers et al., 2020).

The extant literature is not only sparse, but also suffers from a critical limitation. Past studies have not controlled for mean levels of affect, which have considerable influence on affect dynamics (Dejonckheere et al., 2019). For example, greater mean score usually leads to greater variability (Dejonckheere et al., 2019; Ebner-Priemer, Eid, Kleindienst, Stabenow, & Trull, 2009). Since high NA is a core feature of the psychosis spectrum (Horan et al., 2008), it is possible that the observed elevated NA variability could be a by-product of elevated mean-level NA. Thus, to clarify whether altered affect dynamics are a specific feature of the psychosis spectrum, it is important to partial out the influence of mean-level affect.

The following three studies comprehensively examined affect dynamic indices in relation to psychosis spectrum symptoms over and above mean levels of affect. To replicate and expand

prior ESM findings, Study 1 modeled affect dynamics from naturally occurring linguistic expressions on a social media platform (i.e., Twitter). Study 2 and Study 3 further probed the effects of timescales and contexts, as the dynamical phenomena at varying timescales and contexts are likely governed by different processes and could show differential relations with psychopathology (Ebner-Priemer & Sawitzki, 2007; Hollenstein, 2015; Hollenstein, Lichtwarck-Aschoff, & Potworowski, 2013; Koval, Pe, Meers, & Kuppens, 2013; Lapate & Heller, 2020). Specifically, Study 2 anchored affect dynamics to a wide range of internal contexts, including a baseline state as well as subjectively meaningful pleasant and unpleasant events. Study 3 applied a finer temporal resolution and stricter control of external contexts by investigating moment-to-moment affective experiences in response to a standardized emotional film clip. All three studies separately examined subthreshold positive and negative symptoms of the psychosis spectrum, as respectively measured by perceptual aberration and magical ideation (Chapman, Chapman, & Raulin, 1978; Eckblad & Chapman, 1983) and social anhedonia (Eckblad, Chapman, Chapman, & Mishlove, 1982). These psychosis-related personality traits that have been shown to predict future psychosis-spectrum development in nonclinical samples (Chapman et al., 1994; Kwapil, 1998; Lenzenweger, 2021), which were used in current studies to elucidate risk for more severe spectrum pathology. Overall, the current research represents an essential step towards uncovering the affect dynamic signatures of psychosis risk.

Study 1

The objective of Study 1 was to test the association between psychosis spectrum symptoms and naturally occurring affect dynamics in spontaneous language expressions on Twitter. For many people, especially young adults, social media has become a part of the daily routine (Hootsuite & We Are Social, 2020). Of particular relevance is the social media language

usage, which has been abundantly demonstrated to reveal psychological states of the user. For example, the extent to which social media posts express positive or negative feelings, or text sentiments, provides a sensitive reflection of the user's emotional states (Fan et al., 2019; Jones, Wojcik, Sweeting, & Silver, 2016; Liu, Zhu, Yu, Rasin, & Young, 2017) and has concurrent and predictive validity in tracking mental and physical health conditions (De Choudhury, Gamon, Counts, & Horvitz, 2013; Eichstaedt et al., 2015, 2018; Reece et al., 2017). This, together with the time-sensitive and low-cost features, makes social media language a rich resource for identifying affect dynamic risk markers of psychosis.

In Study 1, we downloaded posts (i.e., tweets) from participants' Twitter timelines and utilized text sentiment of the tweet as a proxy for their affective experience in that moment. Based on previous ESM findings, we expected that positive symptoms would be associated with greater sentiment variability and instability, particularly for NA, while social anhedonia would be associated with greater sentiment inertia. We also explored the association of positive symptoms and social anhedonia with three other dynamic indices due to their theoretical relevance, namely emodiversity, density, and synchrony.

Method

Participants

Participants were undergraduate students who, as part of a larger online study, provided a valid Twitter username and completed scales for psychosis spectrum symptoms. They received course extra credit for completing the study that was administered via Qualtrics (Qualtrics, Provo, UT). This study was approved by the University's Institutional Review Board.

There were 1,291 participants who completed the online study, after removing people with extremely careless or invalid responses (167 removed) and those reported having never

used Twitter (932 removed). Participants were then asked to provide their Twitter username, of which 1,162 (90.01%) were excluded due to refusal (1,093 excluded), having a private or suspended account (50 excluded), and having insufficient tweets (i.e., < 10 ; 19 excluded). The final sample size consisted of 129 participants (see Table 2 for participant characteristics for Study 1-3). Compared to the excluded participants, included participants had greater positive symptoms, $t(1289) = 2.04$, $p = .042$, $d = 0.19$, and lower social anhedonia, $t(1289) = -2.02$, $p = .044$, $d = 0.19$. Nevertheless, differences in psychosis spectrum symptoms, although statistically significant, were small in magnitude.

Power analysis indicated that the current sample size had 80% power to detect a small-to-medium effect of $r = .24$. This is sufficient to test the primary hypotheses of the current study based on previous ESM findings using nonclinical samples (e.g., $r = .24$ for the association between positive symptoms and NA variability; Kwapil et al., 2012). In addition, meta-analytic effect sizes ranged from $r = .24$ to $r = .36$ for the association of various psychopathological symptoms with NA variability and instability (Houben et al., 2015).

Table 2

Participant Demographic Characteristics and Psychosis Spectrum Symptoms

	Study 1	Study 2	Study 3
<i>N</i>	129	154	154
Female <i>n</i> (%)	108 (83.72)	114 (74.02)	130 (84.42)
Age <i>M</i> (<i>SD</i>)	20.27 (3.08)	21.32 (4.24)	20.92 (4.42)
Race <i>n</i> (%)			
African American	6 (4.65)	4 (2.60)	2 (1.30)
Asian	45 (34.88)	66 (42.86)	63 (40.91)
European American	25 (19.38)	25 (16.23)	32 (20.78)
Latinx	37 (28.68)	47 (30.52)	38 (24.68)
Other	16 (12.40)	12 (7.79)	19 (12.34)
Country of Origin: U.S. <i>n</i> (%)	107 (82.94)	121 (78.57)	110 (71.43)
Psychosis Spectrum Symptoms			
Perceptual Aberration <i>M</i> (<i>SD</i>) [range]	1.13 (1.90) [0-10]	1.09 (2.16) [0-13]	1.71 (2.78) [0-11]
Magical Ideation <i>M</i> (<i>SD</i>) [range]	3.18 (2.65) [0-11]	2.69 (2.81) [0-13]	3.76 (3.41) [0-13]
Social Anhedonia <i>M</i> (<i>SD</i>) [range]	2.37 (2.35) [0-12]	2.28 (2.41) [0-10]	3.28 (3.35) [0-12]

Materials

Psychosis spectrum symptoms. Psychosis spectrum symptoms were assessed with the short versions of the Wisconsin Schizotypy Scales (Winterstein et al., 2011). The 15-item Short Perceptual Aberration Scale ($\alpha = .76$) and the 15-item Short Magical Ideation Scale ($\alpha = .72$) measure perceptual distortions and unusual beliefs, respectively (e.g., “Parts of my body occasionally seem dead or unreal”; “I have occasionally had the silly feeling that a TV or radio broadcaster knew I was listening to him”). As in previous research (e.g., Kerns, Docherty, & Martin, 2008), a single positive symptom score was calculated by summing the standardized scores of perceptual aberration and magical ideation. The 15-item Short Revised Social Anhedonia Scale ($\alpha = .72$) measures lack of relationships and lack of pleasure from relationships (e.g., “Having close friends is not as important as many people say”). Scores on the Wisconsin

Schizotypy Scales have shown high correspondence with clinician-rated psychosis spectrum symptoms (i.e., the Structured Interview for Prodromal Syndromes; Cicero, Martin, Becker, Docherty, & Kerns, 2014) and are predictive of future development of psychosis-spectrum disorders (Chapman et al., 1994; Kwapil, 1998; Lenzenweger, 2021). The short, rather than full, versions of these scales were chosen due to their superior psychometric properties (Cicero, Martin, & Krieg, 2019; Li, Cicero, Dodell-Feder, Germine, & Martin, 2021).

Twitter data processing. Using Twitter’s Application Programming Interface (API), tweets (up to the most recent 3,200) were downloaded on November 1, 2020. On average, participants contributed 644.59 tweets ($SD = 670.85$, range = 11-2713) elapsing across 210.24 weeks ($SD = 113.14$, range = 8.71-516.71). There was a large variation in the frequency of posting tweets, with the average time interval between successive tweets ranging from 2.21 hours to 24.24 weeks ($M = 1.42$ weeks, $SD = 2.91$ weeks).

After basic preprocessing (Silge & Robinson, 2017; see supplementary materials for details), sentiment analysis was conducted using the Valence Aware Dictionary and sEntiment Reasoner (VADER; Hutto & Gilbert, 2014). VADER uses dictionary and rule-based model to extract sentiment polarity and intensity and is especially sensitive to social media text. It has been shown to outperform other established automatic sentiment analytic tools (e.g., Linguistic Inquiry and Word Count) and even individual human raters (Hutto & Gilbert, 2014). For each tweet, an overall sentiment valence score was estimated by summing the valence score of each word in the VADER dictionary, adjusted by rules such as negations (e.g., “not” and “wasn’t”) and degree modifiers (e.g., “very” and “kind of”), and normalized to be between -1 (most negative) and 1 (most positive). The proportion of text that were positive or negative was also estimated, which are hereinafter referred to as positive and negative sentiment respectively. Of

note, positive and negative sentiments only represent the categorization of individual words into positive and negative classes and, unlike overall sentiment, do not take into account sentiment strength and rule-based adjustments (e.g., negations, degree modifiers). Lastly, the frequency of unique sentiment-expressing words (i.e., those that matched words in the VADER dictionary) was tallied for each participant. All processing steps were carried out in Python using custom scripts (available online at <https://osf.io/bu2rs/>).

Affect dynamic indices. Affect dynamic indices were computed using the methods described in Table 1. All indices were computed separately for overall sentiment, positive sentiment only, and negative sentiment only, except for density and synchrony, which were computed based on the relations between positive and negative sentiments. Due to the unequal time intervals between successive tweets, adjustments were made for time-reliant indices, namely instability, inertia, and density. For instability measures, adjusted successive differences (ASDs) were computed by dividing successive differences (SDs) by $[(\text{time}_i - \text{time}_{i-1}) / \text{Mdn}(\text{time}_i - \text{time}_{i-1})]^\lambda$, where $\text{Mdn}(\text{time}_i - \text{time}_{i-1})$ is the median time interval for all i s (Jahng et al., 2008). A value of λ was chosen so that the expected absolute ASDs across time intervals, obtained via lowess, were as constant as possible. The ASDs were used for the subsequent calculation of square successive difference (SSD) and acute change (AC). For inertia, time since first tweet was added as a covariate in a multilevel model that simultaneously estimated the moderating role of positive symptoms and social anhedonia in individual differences in the sentiment's autocorrelation (detailed below). Similarly for density, time since first tweet was added as a covariate in the multilevel vector autoregressive models, which provided estimates for the population or average sentiment network across participants as well as participant-specific slopes for the calculation of density scores (Bringmann et al., 2016).

Data Analytic Strategy

All analyses were performed using R (R Core Team, 2020). Separate linear regressions were fitted to examine the effect of positive symptoms and social anhedonia on mean-level sentiment and all affect dynamic indices except for instability and inertia. Instability indices were examined using generalized multilevel models with positive symptoms and social anhedonia as predictors and random intercepts of participants. Specifically, SSD was modeled by a gamma error distribution and log link, while AC was modeled by a binomial error distribution with one trial and logit link (Jahng et al., 2008). Inertia was fitted by a multilevel model to examine whether positive symptoms and social anhedonia moderate the autoregressive slope of sentiment at time_{*i*} predicted from its past state at time_{*i-1*}, with random intercepts of participants and random slopes of sentiment at time_{*i-1*} (Kuppens et al., 2010). To test a specific relation with psychosis spectrum symptoms, all models included demographic variables (i.e., gender, age, and race/ethnicity) as covariates. In models involving dynamic indices, mean-level sentiment was also added as a covariate.

Results

Population Sentiment Network

Figure 1a shows the population sentiment network. Similar to affect ratings collected using ESM (e.g., Bringmann et al., 2016), the expressed sentiments on Twitter exhibited excitatory self-loops and an inhibitory edge from positive to negative sentiment, but not vice versa. Thus, the expression of positive sentiment at one tweet was linked to greater expression of positive sentiment and lower expression of negative sentiment at the next tweet. In contrast, the expression of negative sentiment at one tweet was linked to greater expression of negative

sentiment at the next tweet, but did not significantly influence the subsequent expression of positive sentiment.

a. Study 1 **b. Study 2** **c. Study 3**

Figure 1. Population sentiment/affect networks for Study 1 Twitter data (a), Study 2 writing data (b), and Study 3 film clip data (c). Numbers represent standardized coefficients β (standard error). Solid edges correspond to excitatory relations and dashed edges correspond to inhibitory relations. Significant relations ($p < .05$) are shown in black color, while nonsignificant relations are shown in gray.

Affect Dynamics and Psychosis Spectrum Symptoms

As shown in Table 3, greater positive symptom scores were associated with elevated variability and instability (both SSD and AC) in overall sentiment. In contrast, greater social anhedonia scores were associated with marginally reduced variability and instability (AC) in overall sentiment, as well as elevated inertia in overall sentiment, positive sentiment, and marginally, negative sentiment. Thus, people who are high in positive symptoms exhibit greater overall and moment-to-moment fluctuations in sentiment valence. Those who are high in social anhedonia exhibit the opposite pattern, showing a greater resistance to change, primarily for positive sentiment, coupled with a trend for reduced sentiment valence fluctuations.

Table 3

Association of Positive Symptoms and Social Anhedonia with Twitter Affect Dynamics

Outcome	Positive Symptoms			Social Anhedonia			Mean Sentiment		
	Estimate (SE)	Test Statistic	p	Estimate (SE)	Test Statistic	p	Estimate (SE)	Test Statistic	p
Mean Sentiment									
Overall	0.014 (0.094)	0.15	.88	0.049 (0.096)	0.51	.61	--		
Positive	0.039 (0.093)	0.42	.67	-0.024 (0.095)	-0.26	.80	--		
Negative	0.041 (0.092)	0.44	.66	-0.076 (0.094)	-0.80	.42	--		
Variability									
Overall	0.24 (0.087)	2.80	.0059	-0.16 (0.089)	-1.80	.074	0.090 (0.085)	1.06	.29
Positive	-0.038 (0.066)	-0.58	.56	-0.091 (0.068)	-1.34	.18	0.68 (0.066)	10.44	<.001
Negative	-0.071 (0.046)	-1.54	.13	-0.0045 (0.047)	-0.096	.92	0.86 (0.046)	18.69	<.001
Instability (SSD)									
Overall	0.020 (0.0062)	3.25	.0012	-0.0091 (0.0064)	-1.42	.15	-0.0064 (0.0050)	-1.26	.21
Positive	-0.0011 (0.0020)	-0.54	.59	-0.0034 (0.0021)	-1.64	.10	0.010 (0.0016)	6.29	<.001
Negative	-0.0013 (0.0011)	-1.11	.27	-0.00035 (0.0012)	-0.29	.77	0.017 (0.0011)	15.38	<.001
Instability (AC)									
Overall	0.10 (0.029)	3.57	<.001	-0.058 (0.031)	-1.90	.057	-0.0081 (0.026)	-0.32	.75
Positive	0.000073 (0.031)	0.0023	1.00	-0.033 (0.033)	-1.00	.32	0.17 (0.026)	6.67	<.001
Negative	-0.017 (0.021)	-0.81	.42	-0.018 (0.023)	-0.76	.45	0.37 (0.024)	15.67	<.001
Inertia									
Overall	-0.0081 (0.0075)	-1.08	.28	0.015 (0.0077)	2.01	.047	0.24 (0.0035)	70.20	<.001
Positive	0.0012 (0.0078)	0.15	.88	0.017 (0.0078)	2.21	.029	0.24 (0.0056)	43.49	<.001
Negative	-0.0067 (0.0046)	-1.44	.15	0.0099 (0.0052)	1.90	.060	0.16 (0.0065)	24.45	<.001
Emodiversity									
Overall	0.072 (0.091)	0.79	.43	0.014 (0.094)	0.15	.88	-0.30 (0.089)	-3.43	<.001
Positive	0.078 (0.094)	0.83	.41	0.00060 (0.096)	0.0062	1.00	-0.15 (0.093)	-1.64	.10
Negative	0.060 (0.090)	0.66	.51	0.028 (0.093)	0.31	.76	0.35 (0.090)	3.89	<.001
Density									
	-0.0022 (0.058)	-0.037	.97	0.090 (0.060)	1.51	.13	Pos: 0.71 (0.060)	11.71	<.001
							Neg: -0.25 (0.061)	-4.07	<.001
Synchrony									
	-0.026 (0.078)	-0.33	.74	0.026 (0.080)	0.32	.75	Pos: -0.52 (0.081)	-6.44	<.001
							Neg: -0.39 (0.082)	-4.81	<.001

Note. Significant and trend-level significant results are highlighted. Estimate refers to the standardized coefficient β of psychosis spectrum symptoms except for (a) square successive difference (SSD), which is the log of SSD; (b) acute change (AC), which is the log odds of AC; and (c) inertia, which is the standardized coefficient for the interaction between psychosis spectrum symptoms and lagged sentiment. Test statistic refers to the t statistic except for SSD and AC, which is the z statistic. Pos = positive sentiment, Neg = negative sentiment.

Discussion

This is the first study to examine affect dynamics in relation to the psychosis spectrum using natural language expressions on Twitter. Building on work by previous ESM studies, the present findings provide evidence that positive and negative symptoms of the psychosis spectrum are respectively characterized by more and less changeable affect in daily life. Findings also demonstrate that the dynamics of affect can be captured by Twitter data and they behave in a similar fashion as data collected using established naturalistic methods. Together, social media data have proved feasible in providing a time-sensitive and cost-effective assessment of affect dynamic markers of psychosis risk and may be a useful supplement to existing screening and monitoring approaches.

Consistent with our hypotheses, positive symptoms were associated with elevated variability and instability in overall sentiment valence, whereas social anhedonia was associated with elevated inertia that was driven by the positive sentiment as well as a trend for reduced valence variability and instability. This suggests that, in terms of longer-timescale mood fluctuations in daily life across various contexts, positive symptoms of the psychosis spectrum are related to a larger amplitude and frequency of valence fluctuations, whereas negative symptoms are related to a greater resistance to change in PA. However, it is worth noting that there are two sources of noise inherent in the Twitter data. In the time domain, there is a large variation in the interval between successive tweets and thus necessitates adjustment for the calculation of time-reliant indices. Additionally, people share their thoughts and feelings via tweets for a variety of reasons, from reacting to emotional events to simply describing their daily routine. This mixture of contexts may attenuate the association between affect dynamics and psychosis spectrum symptoms that might be only apparent under emotional provocations (Lapate

& Heller, 2020; Myin-Germeys & van Os, 2007). At the same time, there may be individual differences in the tendency to post tweets under one type of situations versus another, potentially meddling the interpretation of the current results. For example, the elevated inertia associated with social anhedonia could be driven by the possibility that people who are high in social anhedonia tend to post about less emotional contents under relatively neutral, baseline states, rather than a resistance to change *per se*. Disentangling the effects of timescales and contexts is therefore crucial in parsing the noise in people's affective time series (Dejonckheere et al., 2019; Lapate & Heller, 2020). This was what we sought to do in Study 2.

Study 2

The objective of Study 2 was to examine the relations between psychosis spectrum symptoms and momentary affect dynamics under baseline, pleasant, and unpleasant contexts. These contexts were experimentally induced in the lab, where participants were asked to provide an unprompted response about their current thoughts (i.e., baseline state) as well as the most pleasant and unpleasant events in their lives. We used sentence-level sentiment as a proxy for their affective experience in that moment and modeled affect dynamics across sentences within each context. In addition, participants were preselected to represent a wide range of positive and negative psychosis spectrum symptoms. Because psychosis risk has been linked to heightened affective reactivity (Myin-Germeys & van Os, 2007), we expected that positive symptoms' elevated variability and instability as well as social anhedonia's elevated inertia would be particularly pronounced under emotionally charged contexts compared to the baseline state. As in Study 1, we also conducted exploratory analyses for the association of positive symptoms and social anhedonia with other affect dynamic indices.

Method

Participants

To ensure adequate variation in psychosis spectrum symptoms, participants were recruited from a large pool of undergraduates based on their scores on psychosis-related personality characteristics. Specifically, facets within the Psychoticism and Detachment domains of the Personality Inventory for *DSM-5* (Krueger, Derringer, Markon, Watson, & Skodol, 2012) were used as selection criteria (Grazioplene, Chavez, Rustichini, & DeYoung, 2016), and those who scored low (i.e., all facet scores ≤ 1) and high (i.e., at least one facet score ≥ 2) were invited to the lab. There were 1,787 participants who completed the online screening survey, after removing people with careless or invalid responses (699 removed) and those declined to be contacted for future research studies (863 removed). Eight hundred and ninety-one participants fulfilled the selection criteria, of which 154 (17.28%) participated and completed the laboratory session (see Table 2 for participant characteristics). Included participants had greater positive symptoms of small magnitude than eligible participants who did not participate in the laboratory session, $t(889) = 2.68, p = .0075, d = 0.24$, but did not significantly differ in social anhedonia, $t(889) = 0.35, p = .72, d = 0.031$. Power analysis indicated that the current sample size had 80% power to detect a small-to-medium effect of $r = .22$, which is sufficient to test the primary hypotheses of the current study.

Materials and Procedure

During the laboratory session, participants rated their baseline affect, followed by a free writing task and two autobiographical memory recall tasks (i.e., pleasant and unpleasant). Participants rated their current affect again immediately following each writing task. Subsequent to affect ratings after the autobiographical memory recall tasks, participants performed a simple

cognitive task (i.e., 80-trial Stroop color word task) to minimize the emotion carryover. Upon completion of both the online screening battery and the laboratory session, participants received course extra credit as compensation. Online questionnaires were administered via Qualtrics (Qualtrics, Provo, UT) and the in-lab tasks were administered via MediaLab (Empirisoft Corporation, New York, NY). This study was approved by the University's Institutional Review Board.

Psychosis spectrum symptoms. Same as Study 1, psychosis spectrum symptoms were assessed with the short versions of the Wisconsin Schizotypy Scales (Winterstein et al., 2011; all α s > .72).

Writing tasks. For the free writing task, participants were instructed to write “whatever comes to mind” (e.g., Fung, Moore, Karcher, Kerns, & Martin, 2017). The autobiographical memory recall tasks were adapted from expressive writing paradigms (e.g., Burton & King, 2004) that instructed participants to write about the most pleasant/unpleasant event they have experienced in their lives. The order of the pleasant and unpleasant conditions was counterbalanced across participants. For all three writing tasks, participants typed their response in a text box that was programmed to be visible for only six minutes. However, participants were told that they had 10 minutes to encourage them to write for the entire time period.

Text entries were segmented into sentences after basic preprocessing (Silge & Robinson, 2017; see supplementary materials for details). On average, participants contributed 13.29 sentences ($SD = 6.91$, range = 1-39) for the free writing condition, 12.15 sentences ($SD = 5.40$, range = 2-31) for the pleasant condition, and 12.99 sentences ($SD = 5.96$, range = 2-32) for the unpleasant condition. Then, sentence-level sentiments (i.e., overall sentiment valence and proportions of positive and negative sentiments) were estimated using VADER and the

frequency of unique sentiment-expressing words was tallied. The calculation of affect dynamic indices were carried out in the same way as Study 1, except that (a) no adjustment of time was made, and (b) for participants who only expressed one sentiment valence (e.g., only expressed positive sentiment in the pleasant condition), their emodiversity for the non-expressed valence (e.g., negative sentiment) and synchrony were set to zero.

Current affect. Current affect was assessed at baseline and immediately after each writing task (i.e., four times). Participants were given 16 positively and negatively valenced words with both high arousal and low arousal levels (e.g., serene, elated, sad, anger). The words have been frequently used in previous research to assess self-reported affect (e.g., Martin, Becker, Cicero, Docherty, & Kerns, 2011). Participants were instructed to rate their feelings at the moment using a 5-point scale (1 = *Not at all*; 5 = *Very strongly*). Ratings within each valence category were averaged to yield a composite score for PA (all α s > .82) and NA (all α s > .85).

Data Analytic Strategy

All analyses were performed using R (R Core Team, 2020). First, as a manipulation check, separate multilevel models were fitted to examine the effect of writing condition on (a) affect ratings (PA and NA) and (b) sentiment expressions (overall, positive, and negative sentiment). Next, separate multilevel models were fitted to examine the effect of positive symptoms and social anhedonia as well as their interactions with writing condition on mean-level sentiment and all affect dynamic indices except for instability and inertia. Instability indices were examined using generalized multilevel models, with SSD modeled by a gamma error distribution and log link and AC modeled by a binomial error distribution with one trial and logit link (Jahng et al., 2008). Inertia was fitted by a multilevel model to examine whether positive symptoms and social anhedonia moderate the autoregressive slope of sentiment at time_{*i*} predicted

from its past state at time $_{i-1}$ as well as their interactions with writing condition. All models included demographic variables (i.e., gender, age, and race/ethnicity) as covariates and random intercepts of participants. Inertia models additionally included random slopes of sentiment at time $_{i-1}$. In models involving dynamic indices, mean-level sentiment was also added as a covariate.

Results

Manipulation Check

Overall, the writing tasks were successful in eliciting the desired emotion and sentiment expression. With respect to current affect, relative to baseline, free writing did not significantly change PA ($p = .27$) or NA ($p = .19$). The pleasant condition increased PA ($p = .04$) and decreased NA ($p < .001$), whereas the unpleasant condition decreased PA ($p < .001$) and increased NA ($p < .001$). With respect to sentiment expressions, relative to the free writing condition, the pleasant condition showed increased overall sentiment valence, increased positive sentiment, and decreased negative sentiment (all $ps < .001$). On the other hand, the unpleasant condition showed decreased overall sentiment valence, decreased positive sentiment, and increased negative sentiment (all $ps < .001$).

Population Sentiment Network

Figure 1b shows the population sentiment network for each writing condition. Overall, the sentiment expressed at one sentence was generally unrelated to the sentiment expressed at the next sentence. There is one notable exception: an inhibitory self-loop was observed for the nontarget emotion in the induction conditions. That is, for the pleasant condition, the expression of negative sentiment at one sentence was linked to lower subsequent expression of negative sentiment; for the unpleasant condition, the expression of positive sentiment at one sentence was

linked to lower subsequent expression of positive sentiment. Closer examination of the text entries showed that participants tend to adopt a narrative form that consisted of multiple points of inflections for the induction conditions (e.g., an event was particularly pleasant/unpleasant during a bad/good day; illustrative examples are provided in Table S1). On the other hand, freely expressed thoughts did not convey predictable patterns of sentiments.

Affect Dynamics and Psychosis Spectrum Symptoms

Estimates for free writing, pleasant, and unpleasant conditions are separately shown in Table 4, with the full multilevel model results shown in supplementary Table S2. For the free writing condition, greater positive symptom scores were associated with (a) more positive autocorrelation in negative sentiment and, marginally, positive sentiment, (b) elevated negative sentiment emodiversity, and (c) marginally elevated synchrony between positive and negative sentiments. On the other hand, greater social anhedonia scores were associated with reduced overall sentiment instability (SSD and marginally for AC). Of note, the interpretation of positive symptoms' association with autocorrelation requires additional consideration. For the free writing condition, positive sentiment's autocorrelation at mean-level psychosis spectrum symptoms was $\beta (SE) = -0.046 (0.021), p = .034$. The more positive autocorrelation associated with positive symptoms therefore represents weaker negative temporal dependency or inertia (e.g., autocorrelation at 1 *SD* below and above the mean of positive symptoms was $\beta (SE) = -0.089 (0.032), p = .0055$ and $\beta (SE) = -0.0024 (0.032), p = .94$, respectively). On the other hand, negative sentiment's autocorrelation at mean-level psychosis spectrum symptoms was $\beta (SE) = -0.0032 (0.024), p = .89$. The more positive autocorrelation associated with positive symptoms therefore represents stronger positive inertia (e.g., autocorrelation at 1 *SD* below and above the mean of positive symptoms was $\beta (SE) = -0.066 (0.037), p = .072$ and $\beta (SE) = 0.058 (0.034), p$

= .090, respectively). Thus, at baseline, people who are high in positive symptoms express diverse negative sentiments that linger and inhibit positive sentiments, while people who are high in social anhedonia express reduced sentiment valence fluctuations across time.

The pattern observed for the free writing condition is in stark contrast to those observed under emotionally charged contexts. For the pleasant condition, greater positive symptom scores were associated with (a) reduced overall sentiment, (b) elevated variability in negative sentiment and, marginally, overall sentiment, (c) more positive overall sentiment autocorrelation, and (d) reduced density. For the unpleasant condition, greater positive symptom scores were associated with elevated overall sentiment as well as elevated variability and instability (SSD) in negative sentiment. In contrast, significant associations with social anhedonia were observed for the pleasant, but not unpleasant, condition, where greater social anhedonia scores were marginally associated more negative overall sentiment autocorrelation. Again, the interpretation of psychosis spectrum symptoms' association with autocorrelation requires considering the autocorrelation at mean level, which was $\beta (SE) = -0.037 (0.022)$, $p = .085$ for the pleasant condition. Therefore, the more positive autocorrelation associated with positive symptoms represents weaker negative inertia (e.g., autocorrelation at 1 *SD* below and above the mean of positive symptoms was $\beta (SE) = -0.087 (0.031)$, $p = .0046$ and $\beta (SE) = 0.011 (0.030)$, $p = .72$, respectively). Alternatively, the more negative autocorrelation associated with social anhedonia represents stronger negative inertia (e.g., autocorrelation at 1 *SD* below and above the mean of social anhedonia was $\beta (SE) = -0.00070 (0.031)$, $p = .98$ and $\beta (SE) = -0.074 (0.030)$, $p = .015$, respectively). Thus, people who are high in positive symptoms exhibit drastic and ambivalent fluctuations when induced to feel and express both positive and negative emotions, while people

who are high in social anhedonia tend to exhibit a temporally dependent and alternating pattern of opposing sentiment valence when induced to feel and express positive emotions.

Table 4

Association of Positive Symptoms and Social Anhedonia with Affect Dynamics Under Free Writing, Pleasant, and Unpleasant Conditions

Outcome	Free Writing		Pleasant		Unpleasant	
	Positive Symptoms	Social Anhedonia	Positive Symptoms	Social Anhedonia	Positive Symptoms	Social Anhedonia
Mean Sentiment						
Overall	-0.019 (0.059)	-0.020 (0.058)	-0.13 (0.059)*	-0.061 (0.058)	0.16 (0.059)**	-0.064 (0.058)
Positive	0.0089 (0.069)	-0.023 (0.068)	-0.096 (0.070)	-0.043 (0.068)	0.11 (0.070)	-0.027 (0.068)
Negative	0.068 (0.065)	-0.033 (0.064)	0.095 (0.066)	0.040 (0.064)	-0.080 (0.066)	0.039 (0.064)
Variability						
Overall	0.091 (0.083)	-0.094 (0.082)	0.15 (0.084)†	-0.0058 (0.082)	0.064 (0.084)	-0.015 (0.082)
Positive	0.056 (0.063)	0.053 (0.063)	0.080 (0.064)	0.065 (0.063)	0.071 (0.064)	-0.094 (0.063)
Negative	0.054 (0.054)	-0.057 (0.054)	0.14 (0.055)**	0.0024 (0.053)	0.16 (0.055)**	-0.027 (0.053)
Instability (SSD)						
Overall	0.0066 (0.0090)	-0.018 (0.0083)*	0.0031 (0.0092)	0.0092 (0.0085)	0.0028 (0.0087)	0.00044 (0.0083)
Positive	-0.0016 (0.0019)	0.0023 (0.0017)	-0.00052 (0.0020)	0.0029 (0.0018)	-0.000068 (0.0018)	-0.0012 (0.0017)
Negative	-0.00096 (0.0013)	-0.00019 (0.0012)	0.00051 (0.0013)	-0.00059 (0.0012)	0.0025 (0.0012)*	-0.0010 (0.0011)
Instability (AC)						
Overall	0.12 (0.080)	-0.15 (0.084)†	-0.060 (0.094)	0.053 (0.077)	-0.025 (0.078)	0.051 (0.069)
Positive	-0.045 (0.086)	0.040 (0.070)	0.047 (0.078)	0.053 (0.074)	0.099 (0.083)	-0.15 (0.11)
Negative	0.063 (0.085)	-0.037 (0.084)	0.14 (0.089)	0.12 (0.094)	0.074 (0.066)	0.073 (0.064)
Inertia						
Overall	0.020 (0.023)	0.024 (0.022)	0.049 (0.021)*	-0.037 (0.022)†	0.0089 (0.018)	-0.0048 (0.019)
Positive	0.043 (0.024)†	-0.0084 (0.021)	0.033 (0.023)	-0.032 (0.022)	0.0067 (0.025)	-0.038 (0.030)
Negative	0.062 (0.026)*	-0.020 (0.026)	-0.018 (0.030)	-0.016 (0.033)	0.026 (0.018)	0.011 (0.018)
Emodiversity						
Overall	0.089 (0.084)	0.026 (0.082)	-0.037 (0.085)	0.029 (0.082)	0.023 (0.085)	0.094 (0.082)
Positive	-0.017 (0.065)	0.066 (0.064)	-0.033 (0.065)	0.016 (0.064)	0.069 (0.065)	0.057 (0.064)
Negative	0.14 (0.060)*	0.0079 (0.059)	0.010 (0.061)	0.035 (0.059)	0.030 (0.061)	0.050 (0.059)
Density	0.023 (0.048)	0.0015 (0.048)	-0.17 (0.048)***	0.013 (0.047)	0.013 (0.048)	0.0088 (0.047)
Synchrony	-0.13 (0.079)†	0.032 (0.078)	-0.021 (0.080)	-0.046 (0.078)	-0.059 (0.080)	0.041 (0.078)

Note. Significant and trend-level significant results are highlighted. Estimate refers to the standardized coefficient β of psychosis spectrum symptoms except for (a) square successive difference (SSD), which is the log of SSD; (b) acute change (AC), which is the log odds of AC; and (c) inertia, which is the standardized coefficient for the interaction between psychosis spectrum symptoms and lagged sentiment. Test statistic refers to the t statistic except for SSD and AC, which is the z statistic.

† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Discussion

Study 2 extended Study 1 by taking into account the effect of emotional contexts on momentary affect dynamics. Consistent with our hypotheses, positive symptoms' more changeable sentiments, demonstrated by elevated variability, instability, as well as reduced inertia and network density, are primarily tied to emotionally charged contexts. This is consistent with a large body of literature showing that positive symptoms of the psychosis spectrum are linked to increased affective reactivity (Myin-Germeys & van Os, 2007). Surprisingly, positive symptoms' baseline sentiment expressions are characterized by the reverse pattern, showing diverse negative sentiments that are persistent over time. This suggests that people who are high in positive symptoms spontaneously engage in prolonged processing of negative information, which is in line with prior self-report findings of increased trait attention to negative emotions (Li, Fung, Moore, & Martin, 2019; Martin et al., 2011). Overall, the present findings provide strong evidence for more changeable affect in response to emotional provocations as a risk signature for positive symptoms of the psychosis spectrum.

At the same time, there were only relatively modest associations for social anhedonia across all contexts. It appears that social anhedonia's less changeable sentiments, demonstrated by reduced instability, are primarily tied to the baseline state. Under the pleasant context, social anhedonia's sentiment expressions are characterized by temporally dependent alternations of opposing valence. Considering that, on average, participants utilized points of inflections to provide contrasts in their stories, this finding indicates that people who are high in social anhedonia use more unpleasant contrasts in their narratives of the pleasant event in a rigid, self-predictable fashion. Therefore, people who are high in social anhedonia do experience PA in response to pleasant materials, but in short bursts that cannot be maintained for extended periods

due to the opposing valence effect. This is consistent with prior work linking social anhedonia to deficits in sustained processing of pleasant stimuli in the lab (Martin, Li, & Castro, 2020) as well as failures to sustain PA coupled with exaggerated diminishing influence of NA on PA in daily life (Strauss et al., 2020; Westermann et al., 2017). Nevertheless, findings for negative symptoms are relatively weak and thus await further replications.

Although automatic sentiment analytic tools such as VADER have been extensively validated (Fan et al., 2019; Hutto & Gilbert, 2014), there are nuances to people's subjective feelings that cannot be captured by text. Mainly, sentiment analysis takes people's linguistic expressions "at face value," yet the same words can be used to communicate very different feelings. For example, one of our participants wrote "this girl quickly became a friend with my best friend!", which seemingly conveyed positive feelings and indeed received a highly positive overall sentiment valence score (0.8977). However, this participant was most likely expressing a negative feeling (e.g., anger and annoyance) because her best friend was pried away from her. Findings, therefore, need to be validated against self-reports, the *sine qua non* assessment of subjective feelings (Quigley, Lindquist, & Barrett, 2014). Further, although the same writing prompts were used across participants, they nonetheless generated responses that vary greatly in content. It could be argued that the characteristics of the event, rather than people's emotional reaction to the event, drive the observed findings (or lack thereof). To address these remaining questions, Study 3 assessed momentary self-reports of affective experiences in response to a standardized emotional stimulus.

Study 3

The objective of Study 3 was to examine momentary affect dynamics in the psychosis spectrum during a standardized emotional film clip that contained a fixed sequence of pleasant

and unpleasant scenes. We used a novel paradigm that continuously assessed affective experiences over the duration of the film clip. In addition, participants were preselected to represent a wide range of positive and negative symptoms of the psychosis spectrum. We expected that results would replicate those obtained in Study 2 under emotional contexts, that is positive symptoms would be associated with elevated variability and instability. Due to the observed modest relations between affect dynamic indices and social anhedonia under emotional contexts, we did not have specific hypothesis for social anhedonia. The association of positive symptoms and social anhedonia with other affect dynamic indices were also explored.

Method

Participants

Participants were recruited from a large pool of undergraduates based on their scores on the short versions of the Wisconsin Schizotypy Scales (Winterstein et al., 2011; all α s > .83). Specifically, those who scored low (i.e., < 0.5 *SD* above the mean) and high (i.e., > 1.5 *SD* above the mean) on the three scales were invited to complete a continuous affect assessment task either in the lab or online¹. Upon completion, participants received course extra credit and monetary compensation. All measures were administered via Qualtrics (Qualtrics, Provo, UT). This study was approved by the University's Institutional Review Board.

There were 2,022 participants who completed the online screening survey, after removing people with careless or invalid responses (922 removed) and those declined to be contacted for future research studies (1,049 removed). One thousand and sixty-two participants fulfilled the

¹ The majority of participants (80.52%) completed the task in the lab. Task format was not significantly related to any outcome measures, except for a marginal difference in SSD (PA–binominal model: $B (SE) = -0.24 (0.13)$, $p = .068$; NA–gamma model: $B (SE) = -0.16 (0.090)$, $p = .072$). Participants who completed the task online had a lower likelihood of non-zero (vs. zero) SSDs in PA and lower magnitude of non-zero SSDs in NA than those who completed in the lab.

selection criteria, of which 167 (15.72%) participated in the continuous affect assessment task. A further 13 participants (7.78 %) were excluded due to (a) failing to watch the film clip to its entirety (8 excluded), and (b) having > 50% missing data (5 excluded). The final sample size consisted of 154 participants (see Table 2 for participant characteristics). Included participants had greater social anhedonia of small magnitude than eligible participants who did not participate or complete the task, $t(195.26) = 2.56, p = .011, d = 0.24$, but did not significantly differ in positive symptoms, $t(191.40) = 1.56, p = .12, d = 0.15$. Power analysis indicated that the current sample size had 80% power to detect a small-to-medium effect of $r = .22$, which is sufficient to test the primary hypotheses of the current study.

Materials

Continuous affect assessment task. Participants watched a 12-minute film clip from the tragicomic movie *Life is Beautiful*, depicting a father's humorous attempts to shield his son from the horrors of a Nazi concentration camp. To provide a coherent story, the film clip included emotionally evocative excerpts from the beginning, middle, and end of the movie that have been shown to elicit positive and negative emotions (Cohen, Callaway, Mitchell, Larsen, & Strauss, 2016; Schaefer, Nils, Philippot, & Sanchez, 2010; available upon request).

Affective experiences were assessed using the evaluative space grid (Larsen, Norris, McGraw, Hawkey, & Cacioppo, 2009). This 5 by 5 grid was composed of PA ratings on the x-axis ("How POSITIVE do you feel?") and NA ratings on the y-axis ("How NEGATIVE do you feel?"), with both ratings made on a 5-point scale (0 = *Not at all*; 4 = *Extremely*). Participants were instructed to use the mouse cursor to continuously indicate their affective experiences in that moment. The cursor appeared outside of the grid at the beginning of the film clip, after which participants were instructed to use the mouse to move the cursor throughout the grid as

fast or slow as they wished. The cell location of the cursor was recorded every 100 ms.

Immediately after the film clip, participants were asked if they were experiencing any emotions right now and, if they indicated yes, to list all emotions in a text box.

Affect ratings were down-sampled to every 1 second offline for the current analysis. Out of the 723 possible assessments (12.05 minutes x 60 seconds/minute x 1 assessment/second), participants contributed 702.98 on average ($SD = 57.47$, range = 433-723). Affect dynamic indices were calculated using the same methods described in Study 1 based on affect ratings and open-ended responses, except that no adjustment of time was made. Additionally, a more stringent cutoff was used for AC. Because the majority of affect ratings did not change from one moment to the next (PA: 93.54%; NA: 93.03%), the cutoff for acute increase was set as any positive change in affect ratings (i.e., PA: top 3.68%; NA: top 3.60%). Lastly, emodiversity was set to zero for participants who did not provide any sentiment-expressing words, and synchrony was set to zero for one participant who did not show any variability in PA.

Data Analytic Strategy

All analyses were performed using R (R Core Team, 2020). Separate linear regressions were fitted to examine the effect of positive symptoms and social anhedonia on mean-level affect and all affect dynamic indices except for instability and inertia. Instability indices were examined using generalized multilevel models with positive symptoms and social anhedonia as predictors and random intercepts of participants. Specifically, SSD was modeled by a multilevel zero-inflated gamma model due to excessive zeros representing no change in affect from one moment to the next (Min & Agresti, 2002; Zuur & Ieno, 2016). This model considered separately (a) the likelihood of obtaining non-zero (vs. zero) SSDs, which was modeled by a binomial error distribution with one trial and logit link, and (b) the magnitude of non-zero SSDs, which was

modeled by a gamma error distribution and log link. AC was modeled by a binomial error distribution with one trial and logit link (Jahng et al., 2008). Inertia was fitted by a multilevel model to examine whether positive symptoms and social anhedonia moderate the autoregressive slope of sentiment at time_{*i*} predicted from its past state at time_{*i-1*}, with random intercepts of participants and random slopes of sentiment at time_{*i-1*} (Kuppens et al., 2010). To test a specific relation with psychosis spectrum symptoms, all models included demographic variables (i.e., gender, age, and race/ethnicity) as covariates. In models involving dynamic indices, mean-level sentiment was also added as a covariate.

Results

Population Affect Network

Average affect ratings showed that the film clip was successful in inducing PA and NA that were largely alternating over the entire duration (see supplementary Figure S1). Correspondingly, the population affect network (Figure 1c) showed strong excitatory self-loops and weaker inhibitory edges between PA and NA.

Affect Dynamics and Psychosis Spectrum Symptoms

As shown in Table 5, greater positive symptom scores were associated with (a) elevated PA, (b) elevated instability (SSD–binomial models and AC), characterized by greater likelihood of changes and large increases in PA and NA, (c) reduced inertia in PA and, marginally, NA, and (d) and elevated emodiversity in negative sentiment and, marginally, overall sentiment. On the other hand, greater social anhedonia scores were associated with (a) reduced PA, (b) reduced NA instability (SSD–gamma model), characterized by lower magnitude of NA changes, and (c) marginally reduced overall emodiversity. Thus, mirroring Study 2 findings under emotionally charged contexts, people who are high in positive symptoms exhibit drastic and ambivalent

fluctuations in their affective experiences during the film clip. People who are high in social anhedonia stably focused on the unpleasant aspect of the film clip and, similar to Study 2 under the unpleasant context, did not show strong patterns of affect dynamics.

Table 5

Association of Positive Symptoms and Social Anhedonia with Film Clip Affect Dynamics

Outcome	Positive Symptoms			Social Anhedonia			Mean Affect		
	Estimate (SE)	Test Statistic	<i>p</i>	Estimate (SE)	Test Statistic	<i>p</i>	Estimate (SE)	Test Statistic	<i>p</i>
Mean Affect									
Positive	0.29 (0.077)	3.74	<.001	-0.17 (0.076)	-2.26	.025	--		
Negative	0.10 (0.081)	1.25	.21	-0.026 (0.080)	-0.33	.74	--		
Variability									
Positive	0.11 (0.076)	1.50	.14	-0.079 (0.073)	-1.09	.28	0.41 (0.078)	5.31	<.001
Negative	0.12 (0.081)	1.47	.14	-0.11 (0.080)	-1.36	.18	0.27 (0.083)	3.23	.0015
Instability (SSD)									
Positive–Binomial	0.15 (0.055)	2.65	.0079	-0.033 (0.054)	-0.61	.54	0.12 (0.058)	2.04	.041
Positive–Gamma	0.010 (0.032)	0.31	.76	-0.036 (0.032)	-1.12	.26	0.15 (0.031)	4.94	<.001
Negative–Binomial	0.17 (0.053)	3.14	.0017	-0.056 (0.053)	-1.05	.29	0.011 (0.055)	0.20	.84
Negative–Gamma	0.037 (0.034)	1.07	.28	-0.073 (0.035)	-2.08	.037	0.039 (0.033)	1.18	.24
Instability (AC)									
Positive	0.13 (0.050)	2.56	.010	-0.039 (0.049)	-0.80	.42	0.090 (0.053)	1.69	.092
Negative	0.14 (0.048)	2.90	.0037	-0.049 (0.049)	-1.00	.32	0.043 (0.051)	0.85	.39
Inertia									
Positive	-0.0017 (0.00077)	-2.21	.029	0.0011 (0.00081)	1.38	.17	0.45 (0.00051)	879.33	<.001
Negative	-0.0015 (0.00090)	-1.69	.092	0.0014 (0.00094)	1.48	.14	0.57 (0.00048)	1193.22	<.001
Emodiversity									
Overall	0.14 (0.085)	1.67	.096	-0.14 (0.081)	-1.75	.081	PA: 0.15 (0.088)	1.70	.091
							NA: 0.089 (0.084)	1.06	.29
Positive	0.044 (0.087)	0.51	.61	-0.11 (0.084)	-1.30	.20	0.16 (0.090)	1.80	.074
Negative	0.22 (0.081)	2.68	.0081	-0.066 (0.080)	-0.82	.41	0.12 (0.082)	1.48	.14
Density	-0.096 (0.086)	-1.12	.26	0.067 (0.082)	0.82	.42	PA: -0.26 (0.088)	-2.98	.0034
							NA: 0.093 (0.084)	1.11	.27
Synchrony	-0.026 (0.086)	-0.30	.76	0.059 (0.082)	0.72	.47	PA: -0.16 (0.088)	-1.82	.071
							NA: -0.30 (0.084)	-3.52	<.001

Note. Significant and trend-level significant results are highlighted. Estimate refers to the standardized coefficient β of psychosis spectrum symptoms except for (a) square successive difference (SSD), which is the log odds of non-zero (vs. zero) SSD for binominal models and the log of non-zero SSD for gamma models; (b) acute change (AC), which is the log odds of AC; and (c) inertia, which is the standardized coefficient for the interaction between psychosis spectrum symptoms and lagged sentiment. Test statistic refers to the *t* statistic except for SSD and AC, which is the *z* statistic. PA = positive affect, NA = negative affect.

Discussion

Study 3 provided the strictest test of the momentary affect dynamics in the psychosis spectrum by tapping into self-reports of affective experiences in response to a standardized emotional stimulus. Largely replicating Study 2 under emotionally charged contexts, Study 3 showed that positive symptoms were associated with elevated instability and NA emodiversity, as well as reduced PA inertia, whereas social anhedonia was related to reduced NA instability. Extending Study 2, Study 3 has the added experimental control of external inputs and directly assessed people's subjective feelings. Thus, positive symptoms' more changeable affect in response to emotional provocations is likely due to endogenous processes that are specific to the pathophysiology of positive symptoms. On the other hand, social anhedonia is characterized by a small reduction in the magnitude of NA fluctuations but otherwise displaying unremarkable disturbances in affect dynamics when reacting to emotional materials.

General Discussion

There is a long tradition of research identifying risk markers in the service of the goal of anticipating and preventing transitions towards psychotic disorders. Nevertheless, current approaches have proved to be less than satisfactory (Fusar-Poli, Sullivan, Shah, & Uhlhaas, 2019). This insufficiency has recently been brought to the forefront with the \$99-million initiative calling to "further define early stages of risk and predict the likelihood of progression to psychosis and other outcomes" (National Institutes of Health, 2020). Given the substantial theoretical and empirical support for affect dynamics in anticipating transitions in psychopathology, the current research provided an initial inquiry into identifying affect dynamic signatures of psychosis risk. Across three studies, we comprehensively examined affect dynamic indices as they relate to positive and negative symptoms of the psychosis spectrum under varying

timescales and contexts both in daily life and in laboratory settings. Collectively, findings provided (a) strong support for heightened magnitude and frequency of affective fluctuations following emotional provocations as a hallmark for positive symptoms, and (b) modest support for greater persistence of baseline states as a hallmark for negative symptoms. Further, these findings are observed over and above mean-level affect, and even in nonclinical samples, underscoring the utility of affect dynamics in capturing, and perhaps predicting, risk for psychosis.

Heightened Affective Fluctuations: Strong Risk Signature for Positive Symptoms

Extending previous ESM findings into the digital space of social media, we showed that positive symptoms were associated with elevated affect variability and instability in daily life. Subsequent studies further showed that elevated variability and instability in both PA and NA were tied to emotional, rather than baseline, contexts. These findings add to the growing knowledge of the affect-reactive profile of positive symptoms, substantiating the affective pathway to psychosis (Myin-Germeys & van Os, 2007). A large body of literature has shown that people with high positive symptoms display marked response to emotional materials (Cohen & Minor, 2010; Li, Dent, et al., 2021; Myin-Germeys & van Os, 2007). Not only observed at the group-level, the increased affective reactivity has been associated with greater concurrent and future experience of positive symptoms within a person (Kasanova, Hajdúk, Thewissen, & Myin-Germeys, 2020; Klippel et al., 2017; Kramer et al., 2014; Krkovic, Clamor, Schlier, & Lincoln, 2020; Simor, Báthori, Nagy, & Polner, 2019). We provided additional insights on the role of altered affect-reactive dynamics in the developmental trajectory of psychosis. Specifically, elevated variability and instability may progressively build up to trigger the onset of clinically significant psychosis. In order to leverage affect dynamics into building individualized

prediction models, future research on within-subject affect time series is needed, such as testing whether windows of rising fluctuations predict exacerbation in positive symptoms down the line.

Interestingly, people who are high in positive symptoms showed a paradoxical increase of nontarget emotions. That is, lower sentiment valence for the pleasant condition, greater sentiment valence for the unpleasant condition, and greater PA and a trend towards greater NA for the mixed-valence film clip. This experience of contradictory emotions at close temporal proximity supports the notion of “schizotypal ambivalence,” a construct that has been assigned considerable theoretical importance but has yet received much empirical attention (Bleuler, 1911; Kwapil, Mann, & Raulin, 2002; Meehl, 1990). Specifically, ambivalence has been suggested to reflect two distinct processes, either (a) simultaneous coactivation of contradictory emotions or (b) rapid change of emotions over time (Raulin & Brenner, 1993). It is currently unclear which process gives rise to ambivalence, contributing to the difficulty and inconsistency in operationalizing this construct in research (Docherty, Cicero, Becker, & Kerns, 2014; Kwapil et al., 2002; MacAulay, Brown, Minor, & Cohen, 2014; Trémeau et al., 2009). Our findings of altered affect intensity, in conjunction with elevated fluctuations in both PA and NA, imply that ambivalence is likely the result of high frequency changes, rather than simultaneous coactivation, for people with high positive symptoms. Thus, the present findings fill an important gap in elucidating the nature of schizotypal ambivalence.

Persistent Baseline States: Modest Risk Signature for Negative Symptoms

In contrast to positive symptoms’ profound alterations in affect dynamics, social anhedonia only showed relatively weak associations, displaying a pattern of reduced variability, instability, and elevated inertia primarily at baseline. Under pleasant and mixed-valenced contexts, social anhedonia additionally showed elevated negative inertia and reduced NA

instability, respectively. This general lack of significant associations is consistent with the handful of studies that examined negative symptoms in relation to affect dynamics in daily life (Kwapil et al., 2012; Oorschot et al., 2013; Westermann et al., 2017). Although we urge caution in interpreting trend-level findings, results seem to indicate that negative symptoms are associated with more persistent affect at baseline, perhaps resulting in difficulties to disengage from NA and sustain PA when reacting to pleasant and mixed-valenced materials. These findings correspond well with previous studies showing that negative symptoms in individuals with schizophrenia were associated with a stronger pull of affect to low PA/high NA baseline states (Strauss et al., 2020; Westermann et al., 2017). Overall, our findings, and that of others, suggest that people with high negative symptoms could only generate short-lived positive feelings, perhaps not powerful enough to serve the function of altering to, and preparing for, potential opportunities in the environment (Ellsworth & Scherer, 2003). As such, a persistent baseline state may underlie motivational and social deficits associated with negative symptoms and thus may be a useful target for improving functional outcomes.

Future Directions

Several important questions remain for future research. Chiefly, we focused on the broad categories of PA and NA and did not examine the myriad of discrete emotions subsumed under these categories. Although examining broad PA and NA dynamics is the commonly adopted approach for past studies, it nonetheless limits our understanding of the dynamics within each valence. For example, there is reason to believe that certain discrete emotions (e.g., anxiety and fear) might be a central node in eliciting positive symptoms (Krkovic et al., 2020). Therefore, mapping the multivariate space of discrete emotions, within and between broad categories of PA and NA, will be a necessary next step in providing a fine-grained understanding of affect

dynamic signatures of psychosis risk. Further, we focused on nonclinical individuals because the interaction between affective and psychotic symptoms are hypothesized to be particularly relevant for the early stage of psychopathology (van Os, 2013). It remains unclear the extent to which current findings generalize to clinical samples. While it has been suggested that the same dynamical pattern underlie both the development and maintenance of psychosis (Ciompi, 2015), future research is clearly warranted.

Conclusions

The current research provides initial evidence that positive and negative psychosis spectrum pathology are signified by distinct alterations in affect dynamics. Findings highlight the importance of distinguishing timescales and contexts in the study of affect dynamics. Broadening the scope of literature, we further demonstrated the feasibility of using various inexpensive laboratory paradigms and preexisting social media text in capturing affect dynamics. This is significant in light of the high demand for training and outreach infrastructure of the prevailing clinical high-risk approach to risk detection. Due to its validity and cost-effectiveness, affect dynamics are poised to be an efficient way to answer the multimillion-dollar question of early risk detection and possibly subsequent prediction and prevention.

Author Contributions

LYL designed the study, performed data analysis and interpretation, and drafted the manuscript under the supervision of EAM. EAM and JS provided critical comments on the manuscript. All authors approved the final manuscript for submission.

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