Does a Latent Class Underlie Schizotypal Personality Disorder? Implications for Schizophrenia

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Despite growing enthusiasm for dimensional models of personality pathology, the taxonic versus dimensional status of schizotypal personality disorder (PD) remains a point of contention in modern psychiatry. The current study aimed to determine empirically the latent structure of schizotypal PD. We examined the latent structure of schizotypal PD in the Psychiatric Morbidity Survey in Great Britain and the second wave of the U.S.-based National Epidemiologic Survey on Alcohol and Related Conditions (NESARC) survey. We analyzed composite indicators created from participant responses using the mean above minus mean below a cut (MAMBAC), Maximum Covariance (MAXCOV), and latent mode factor analysis (L-Mode) taxometric procedures. We also analyzed item-level responses using two latent variable mixture models—latent class analysis and latent class factor analysis. Taxometric and latent variable mixture analyses supported a dimensional, rather than taxonic, structure in both epidemiological samples. The dimensional model better predicted psychosis, intellectual functioning, disability, and treatment seeking than the categorical model based on *DSM–IV* diagnosis. People meeting criteria for schizotypal PD appear to exist on a spectrum of severity with the rest of the population. The possible dimensionality of schizotypal PD adds to growing support for a dimensional structure of PDs including other Cluster A disorders.

Keywords: schizotypal personality disorder, schizophrenia, taxometrics, latent variable mixture modeling, psychosis

Historical observers have used labels like schizoid, ambulatory schizophrenia, borderline schizophrenia, and pseudoneurotic schizophrenia to describe the existence of attenuated or less severe forms of schizophrenia within the family pedigree of individuals with schizophrenia (Miller, Useda, Trull, Burr, & Minks-Brown, 2001). There remains interest in subthreshold manifestations of psychosis as symptoms and features observable in the initial prodomal phase of schizophrenia, as behavioral indicators in ultrahigh risk (UHR) groups, as manifestations of schizotypy, and as features of schizotypal personality disorder (PD). Schizotypal PD is firmly established as a schizophrenia spectrum disorder—studies demonstrate its genetic relationship with schizophrenia and suggest that it is the most prevalent psychiatric disorder among biological relatives of people with schizophrenia (e.g., Kendler,

Myers, Torgerson, Neale, & Reichborn-Kjennerud, 2007). Parallel etiological, neurodevelopmental, neurobiological, and neurocognitive processes underlie the phenomenological similarities between schizotypal PD and schizophrenia (Siever & Davis, 2004). There is evidence that the relationship between schizotypal PD and schizophrenia may reflect a form of heterotypic continuity in which the emergence of schizotypal PD during the prodromal phase precedes the onset of schizophrenia (Bedwell & Donnelly, 2005; Raine, 2006). Schizotypal PD is associated with neurocognitive deficits—attention, working memory, processing speed, and executive functions—shared with schizophrenia and likely contributing to its etiology (Hawkins et al., 2008; Woods et al., 2009).

Paul Meehl's now-classic neurodevelopmental model of schizophrenia (Meehl, 1962, 1989, 1990) provided an etiological context for schizophrenia diathesis, the role of biopsychosocial risk factors in determining its gradient of expressivity, and the existence of clinical and subclinical entities as outcomes of psychometric risk. Meehl posited that several genetic and social learning variables operate on the foreground of a single dominant gene of large autosomal effects that produced *schizotaxia*—a neurodevelopmental organization of the brain characterized by neural integrative deficits, synaptic disconnectivity, cognitive slippage, and a ubiquitous neuronal aberration. Meehl argued that schizophrenia is primarily a neurological disorder of genetic origin and secondarily psychiatric; the *schizogene* is completely penetrant for neurological aberration and incompletely (10%) penetrant for clinical schizophrenia. Meehl used the term *schizotypy* to describe the

observed personality and behavioral organization that results from the interaction of genetic and social learning regimes that contribute to schizophrenia. The expressivity gradient of schizotypy ranges in severity from nonpathology through diagnostically subthreshold presentations, to schizotypal PD, and then schizophrenia.

One assertion of Meehl's theory is that schizophrenia diathesis is discontinuously distributed—an individual is either at risk by virtue of inheriting a necessary genetic predisposition or not. This suggests that, by extension, schizotypy is dichotomous with individuals classified as "schizotypes" or "nonschizotypes" (Lenzenweger, Maher, & Manschreck, 2005). Similarly, the Holzman–Matthysse model suggested that a "latent trait" that codes for both eye-tracking dysfunction and schizophrenia is discontinuously distributed in the population (Holzman et al., 1988). The latent structure implication of Meehl's discontinuity hypothesis of schizotypy for schizotypal PD is somewhat unclear, given the orthogonal histories of both constructs. Meehl (1990) noted that schizotypy was not isomorphic with the *DSM-IV-TR* (American Psychiatric Association, 2000) schizotypal PD, although it may underlie vulnerability to or encompass the latter (along with other Cluster A and C personality features). On the one hand, it may be argued that the taxonicity of schizotypy implies that its clinical expressions, such as schizophrenia and schizotypal PD, represent discrete entities that exist within nonarbitrary boundaries, separating people with from people without the clinical syndrome. Conversely, it may be argued that the latent structure of schizotypy has no implications for schizotypal PD, because the earlier represents a latent personality organization, whereas the latter represents the clustering of phenotypic manifestations, some, but not all, of which may be linked to schizotypy (Lenzenweger et al., 2005). To the degree that individuals with schizotypal PD carry the latent liability, however, they do represent valid putative *schizotypes*.

Gottesman's multifactorial threshold model suggested an additive effect of multiple genetic and environmental factors that result in a dimensional distribution of risk. It also suggested the presence of a "threshold effect," in which individuals falling above the threshold develop clinical schizophrenia (Gottesman & Shields, 1972). Although Gottesman's model viewed latent liability in a dimensional way (and perhaps, by extension, schizotypy), much like Meehl's theory, it posited the emergence of a latent class of decompensated individuals.

Dimensional models of schizotypy and schizophrenia spectrum disorders are not without their proponents. Eysenck's (1993) description of *psychoticism* was in keeping with his prior descriptions of neuroticism and extraversion as normal personality dimensions. Eysenck viewed psychoticism as a third personality dimension and a normal behavioral variation that existed on a severity spectrum with schizophrenia spectrum disorders and contributed to schizophrenia liability. Claridge and colleagues (Claridge, 2006; Claridge & Beech, 1995) proposed that a dimension of schizotypy interacts with genetic and environmental factors to yield two possible outcomes. The first is a dimensional distribution of schizophrenia phenotypes within the schizophrenia spectrum that includes schizotypal PD (quasi-dimensional model). The second is similar to Eysenck's model and posits that schizotypy contributes to an expressivity gradient of schizophrenia, ranging from variations in predisposing traits (e.g., subclinical psychosis) to clinical syndromes at the severe end of the spectrum (fully dimensional model). Claridge's dimensional model makes predic-

tions (by implication) about the latent structure of schizophrenia spectrum disorders—it argues that dimensional phenotypes exist exclusively or in tandem with taxonic phenotypes in the schizophrenia spectrum.

The question about whether schizotypal PD is really taxonic is one of particular salience to the current organization of schizotypal PD and other PDs in the current *DSM-IV-TR*. Many authors have called for a replacement of the current categorical approach with a dimensional one, driven by perceived limitations of categorical models of PDs, including high rates of diagnostic co-occurrence among PDs, frequent subthreshold and "PD not otherwise specified" cases, and the limited construct validity of categorical models (Widiger & Simonsen, 2005; Widiger & Trull, 2007). Further, it has been frequently observed that dimensional models of PDs better predict clinically relevant variables such as treatment seeking and functional disturbance (Morey et al., 2007). Dimensional representations of PDs are not just viable (Shedler & Westen, 2004), but direct evidence that most PDs are dimensional rather than taxonic has recently permeated the literature in the form of taxometric investigations (Haslam, 2011).

Meehl and colleagues developed taxometric methods to distinguish between taxonic and dimensional constructs (Grove & Meehl, 1993; Meehl, 1995; Meehl & Yonce, 1994, 1996; Waller & Meehl, 1998). These methods identify the underlying latent structure through mathematical modeling and graphical depiction of the pattern of relationships among indicators of the construct investigated. The graphical signatures are accompanied by numerical fit indices and consistency tests interpreted within a multiple-hurdles framework that requires convergence from multiple taxometric methods (Meehl, 1995). Most taxometric studies have supported a dimensional structure for *DSM-IV-TR* PDs (Haslam, 2011), but until recently, taxometric studies of Cluster A PDs were missing. It was always conceivable that Cluster A PDs may be taxonic, given their perceived genetic relationship and phenomenological overlap with schizophrenia (Kendler et al., 2007; Siever & Davis, 2004). There are currently only three taxometric studies of Cluster A PDs. All three studies investigated paranoid PD and found it to be dimensional (Ahmed, Green, Buckley, & McFarland, 2012; Arntz et al., 2009; Edens, Marcus, & Morey, 2009). Only one of the three studies investigated schizoid PD and found it to be similarly dimensional (Ahmed, Green, et al., 2012).

Whereas many taxometric studies have investigated the structure of schizotypy, there has been only one direct test of the structure of *DSM*-defined schizotypal PD. Tyrka and colleagues (1995) conducted taxometric analyses on indicators of schizotypy that they believed were equivalent to or overlapped with criteria for schizotypal PD in the third edition (revised) of the *DSM* (*DSM–III–R*; American Psychiatric Association, 1980). The final study indicators included social withdrawal, social anxiety, passivity, flat affect, peculiarity, and prognosis assessed through psychiatric interviews and school reports. Taxometric analyses of the indicators using consistency tests, covariance curves, and Bayesian posterior probabilities produced evidence of a taxonic structure.

Taxometric studies of schizotypy have tended to support a taxonic structure for schizotypy and most of its subcomponents, including perceptual aberration (Horan, Blanchard, Gangestad, & Kwapil, 2004; Korfine & Lenzenweger, 1995), asociality/schizoid withdrawal, and social anhedonia (Blanchard, Horan, & Collins, 2005). In contrast, other conjectured subcomponents, such as hy-

pohedonia and magical ideation, appear dimensional (Horan et al., 2004; Linscott, 2007; Meyer & Keller, 2001). It appears that if schizotypy is taxonic, schizotypal PD should, by extension, be taxonic, given that it represents a severe expression of schizotypy. Despite the apparent verisimilitude of an underlying latent class in schizotypy, a recent study in a nonclinical sample produced evidence of a dimensional structure (Rawlings, Williams, Haslam, & Claridge, 2008). Rawlings and colleagues interpreted their taxometric curves with the aid of simulated comparison data and the comparison curve fit index (CCFI). They suggested that a reconsideration of the early taxonic findings regarding schizotypy is warranted, due to the effects of sample characteristics (e.g., small sample sizes, indicator skew, dichotomous indicators) in previous studies that may increase risk for false taxonic inferences. Beau-

chaine, Lenzenweger, and Waller (2008) took exception to Rawlings and colleagues' assertion on philosophical, conceptual, and methodological grounds, arguing that certain limitations, such as the use of a college sample, rating scales, and sample-specific simulations with taxometric methods, may limit the ability to detect taxonicity. This lively debate highlighted divisions in the taxometric community about the nature of schizotypy in its relation to schizophrenia and the correct implementation of taxometric methods and their limitations. Taxometric investigations of the taxonic versus dimensional status of schizotypal PD test the implication of views regarding schizotypy. They could inform about the place of schizotypal PD in Meehl's original hypothesis—do *DSM–IV* schizotypal PD criteria identify a latent class that conforms to Meehl's theory? They could also serve as a direct test of

Table 1

Items Used, Scale Location, and Endorsement Rates

Survey	Scale	Loading	Endorsed	Not endorsed
ONS items				
Have you had personal experiences with the supernatural?	Perceptual	0.726	12.70	87.30
Do you often see auras or energy fields around people?	Perceptual	0.547	2.20	97.80
Does it seem that objects or shadows are really people or animals or that noises are actually people's voices?	Perceptual	0.427	2.90	97.10
Have you had the sense that some person of force is around you, even though you cannot see anyone?	Odd Beliefs	0.725	18.20	81.80
Do you believe that you have a "sixth sense" that allows you to know and predict things that others can't?	Odd Beliefs	0.704	12.20	87.80
Do you often get the feeling that things that have no special meaning to most people are really meant to give you a message?	Odd Beliefs	0.433	6.30	93.70
Have you ever felt that you could make things happen just by making a wish or thinking about them?	Odd Beliefs	0.440	17.50	82.50
When you are around people, do you often get the feeling that you are being watched or stared at?	Social/Interpersonal	0.805	10.20	89.80
When you are out in public and see people talking, do you often feel that they are talking about you?	Social/Interpersonal	0.798	6.90	93.10
Do you often feel nervous when you are with other people?	Social/Interpersonal	0.635	17.50	82.50
Are there very few people that you're really close to outside of your immediate family?	Social/Interpersonal	0.895	54.10	45.90
NESARC items				
Have you had trouble expressing your emotions and feelings?	Social/Interpersonal	0.763	13.50	86.50
Have you rarely shown emotion?	Social/Interpersonal	0.806	16.50	83.50
Have you often felt nervous when you are with other people even if you have known them for awhile?	Social/Interpersonal	0.458	6.50	93.50
Have you felt suspicious of people, even if you have known them for awhile?	Social/Interpersonal	0.427	12.70	87.30
When you are around people, have you often had the feeling that you are being watched or stared at?	Social/Interpersonal	0.375	9.60	90.40
Have there been very few people that you're really close to outside of your immediate family?	Social/Interpersonal	0.504	32.10	67.90
Have people thought you act strangely?	Disorganization	0.903	8.10	91.90
Have people thought you have strange ideas?	Disorganization	0.848	12.50	87.50
Have people thought you are odd, eccentric or strange?	Disorganization	0.780	10.60	89.40
Have you had personal experiences with the supernatural?	Cognitive/Perceptual	0.744	8.90	91.10
Have you had the sense that some force is around you, even though you cannot see anyone?	Cognitive/Perceptual	0.716	18.60	81.40
Have you believed that you have a "sixth sense" that allows you to know and predict things that others can't?	Cognitive/Perceptual	0.712	9.20	90.80
Have you often seen auras or energy fields around people?	Cognitive/Perceptual	0.635	2.80	97.20
Have you ever felt that you could make things happen just by making a wish or thinking about them?	Cognitive/Perceptual	0.424	7.10	92.90
Have you often had the feeling that things that have no special meaning to most people are really meant to give you a message?	Cognitive/Perceptual	0.355	9.70	90.30
Have you often thought that objects or shadows are really people or animals, or that noises are actually people's voices?	Cognitive/Perceptual	0.273	1.80	98.20

Note. $N = 8,393$ for the ONS; $N = 34,653$ for the NESARC. Scale locations are based on PCA with promax rotation. NESARC = National Epidemiologic Survey on Alcohol and Related Conditions; ONS = Office of National Statistics.

Claridge's fully dimensional model of the expressivity gradient of schizotypy that encompasses subclinical experiences at the low end to schizotypal PD and other schizophrenia spectrum disorders at the severe end of the gradient. The existence of a schizotypal PD taxon may also lend credence to the categorical representation of schizotypal PD in the *DSM* and clarify its relationship to other Cluster A disorders.

We examined the latent structure of schizotypal PD in two epidemiological surveys using taxometric methods supported with consistency tests. We supplemented the use of taxometric methods by taking advantage of recent advances in latent variable mixture modeling that similarly allow competing categorical versus dimensional hypothesis to be tested. Latent variable mixture models of interest were latent class analysis and latent class factor analysis (a simple specification of the family of factor mixture models), which are interpreted with the aid of numerical fit indices and observations of item endorsement patterns.

Method

Participants

We obtained 8,393 participants from the Office of National Statistics' (ONS) 2000 Survey of Psychiatric Morbidity in Great Britain (Singleton, Bumpstead, O'Brien, Lee, & Meltzer, 2001). The survey gathered information about the prevalence of various psychiatric disorders among individuals aged 16 to 74 years randomly selected within private households. Various psychiatric symptoms were assessed including psychosis, PDs, and cognitive functioning. We dropped 187 cases from the original 8,580 who participated in the survey because diagnostic information about schizotypal PD status was unavailable for these individuals in the survey. About 55.3% of the respondents were women, 94.4% were White, 2.1% were Black (West Indian/African), 1.8% were Asian or Oriental (Indian/Pakistani/Bangladeshi), and 1.6% were classified in an "Other" category. In all, 222 individuals met diagnostic criteria for schizotypal PD in the ONS survey.

We also analyzed the responses of 34,653 individuals living in the United States who completed the second wave of the National Institute on Alcohol Abuse and Alcoholism (NIAAA) National Epidemiologic Survey on Alcohol and Related Conditions (NESARC) survey (Grant, Kaplan, & Stinson, 2005). The NESARC surveys were completed in two waves by noninstitutionalized

individuals aged 18 and over residing in private households. The first wave was completed in 2001–2002 and the second wave was completed in 2004–2005. Both waves of the survey assessed *DSM–IV* criteria for a range of psychiatric disorders. Schizotypal PD was assessed in the second wave of the NESARC. About 58% of those who completed the second wave were women, 18.35% were Hispanic/Latino, and 19.70% were Black/African American. A total of 1,534 individuals were classified as meeting *DSM–IV* schizotypal PD criteria.

Measures

The PDs section of the ONS comprised items drawn from the Structured Clinical Interview for *DSM–IV* Axis II (SCID-II; First, Gibbon, Spitzer, Williams, & Benjamin, 1997). This was one of two sections of the survey that was completed in two stages—the first stage interview was administered by lay interviewers and participants also completed the self-report screening instrument. A random sample of individuals who screened positive or negative for personality disorders were followed up with an expert interview. The psychotic disorders section comprised items drawn from the Schedule for Clinical Assessment in Neuropsychiatry (SCAN; Rijnders, van den Berg, Hodiamont, Nienhuis, Furer, & Giel, 2000). A two-stage approach was also implemented to assess psychosis status. First, lay interviewers assessed as part of psychiatric history, report of symptoms, antipsychotic medication use history, hospitalization history, and responses on the five-item Psychosis Screening Questionnaire (PSQ; Bebbington & Nayani, 1995). Individuals whose responses suggested psychosis completed the second stage of the interview, during which the SCAN is administered by psychologists trained to administer it. Individuals who screened positive and were determined as such using the SCAN were classified as "probably psychosis." On occasions when the second stage was not completed (perhaps because the individual refused), "probably psychosis" classification was assigned if such individuals screened positive on multiple Stage 1 criteria. Individuals who screened negative for psychosis during the first-stage screening but agreed to a follow-up interview were also interviewed during the second stage if they screened positive for any personality disorder. In addition, a sample of individuals who screened negative for personality disorders and/or psychosis were also administered the second-stage interview. Of the 7,825 individuals who screened negative during the first stage, 791 were further interviewed during the second stage. Of the 791 cases, two

Table 2
Descriptive Statistics, Separation, and Nuisance Correlations for Candidate Indicators

Survey	M	SD	Skew	Kurtosis	Separation Cohen's d	Taxon	Correlation complement	Full
ONS								
Odd beliefs	0.54	0.90	1.80	2.85	2.26	−0.12	0.24	0.32
Social/interpersonal	0.89	0.94	1.29	1.75	3.26			
Perceptual aberrations	0.18	0.46	2.88	9.30	1.76			
NESARC								
Disorganization	0.35	0.90	3.14	11.10	2.99	0.147	0.24	0.44
Cognitive/perceptual	0.62	1.23	2.99	12.57	2.74			
Social/interpersonal	1.06	1.59	2.40	7.80	3.36			

Note. N = 8,393 for the ONS; N = 34,653 for the NESARC. NESARC = National Epidemiologic Survey on Alcohol and Related Conditions; ONS = Office of National Statistics.

Categorical Comparison Data

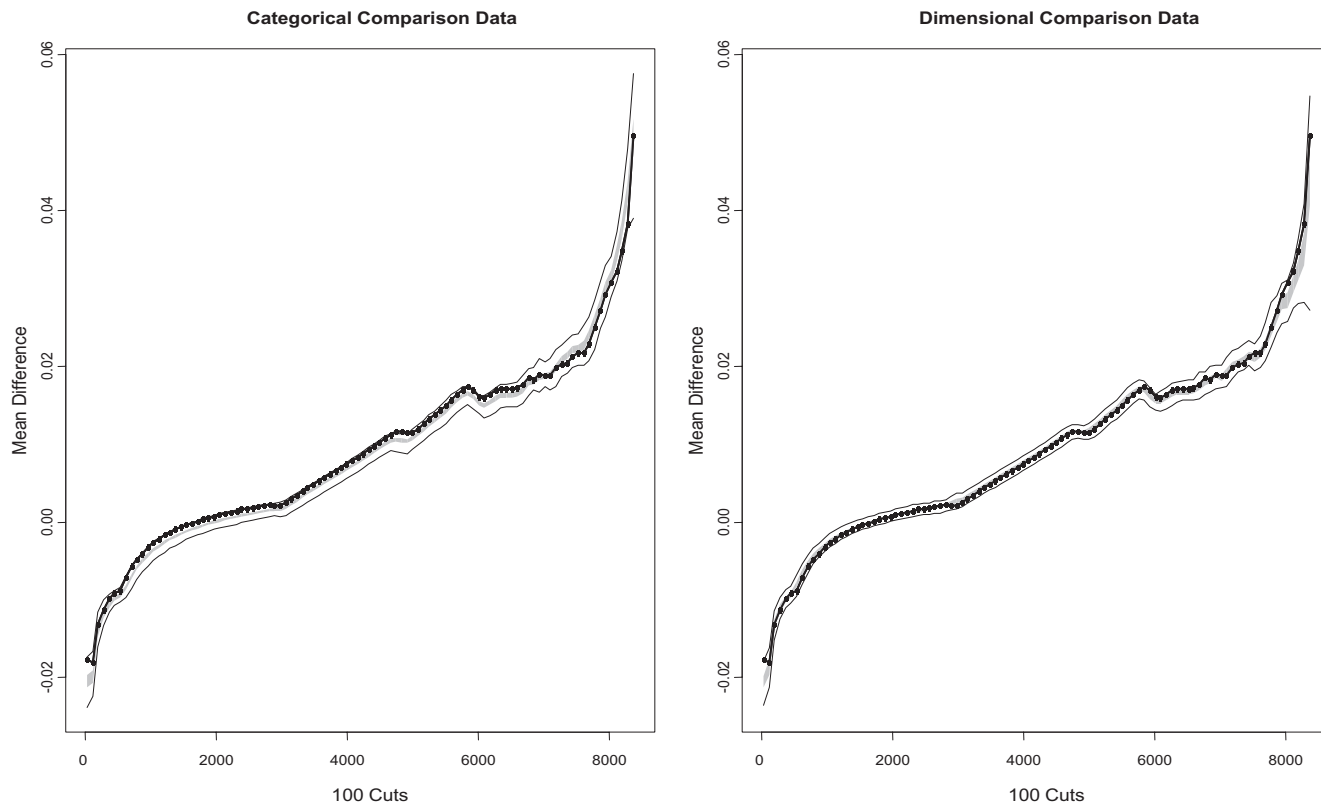**Dimensional Comparison Data**

Figure 1.   Averaged MAMBAC curve for the ONS data juxtaposed over categorical and dimensional comparison simulations in the left panel and dimensional comparison simulations in the right panel.

individuals were later reclassified as "probably psychosis." Intellectual functioning was assessed in the survey using the New Adult Reading Test (NART; Nelson, 1982). Whereas most of the survey was administered by lay interviewers, the SCID-II and the SCAN were administered by expert interviewers.

The NESARC survey items were drawn from the NIAAA Alcohol Use Disorders and Associated Disabilities Interview Schedule–*DSM–IV* Version (AUDADIS-IV). Grant, Dawson, and Hasin (2004) developed the AUDADIS to be administered by trained lay interviewers. The authors have noted that the personality disorders section of the measure was developed to be conceptually similar to well-established PD measures such as the SCID-II and the International Personality Disorders Examination (IPDE; Lorranga et al., 1994). The reliability of the schizotypal PD section of the measure has been reported as .67 in smaller samples (Ruan et al., 2008). The internal consistency of the schizotypal PD section of the NESARC data is .83, which supports the reliability of the measure in the NESARC. The survey included two interview items asking respondents whether they had been informed by a health professional that they had schizophrenia or a psychotic disorder. These items were used as indices of "probable schizophrenia and psychotic episodes." Both the ONS and the NESARC survey included the well-established World Health Organization (WHO) quality of life measure—the 12-Item Short-Form Health Survey, Version 2 (SF-12v2; Ware, Kosinki, & Keller, 1996)—which assesses physical, mental, and psychosocial functioning.

Data Analysis

Taxometric analysis.   To determine the latent structure of schizotypal PD in the epidemiological survey, we analyzed responses using taxometric procedures developed by Meehl and colleagues (Meehl & Yonce, 1994, 1996; Waller & Meehl, 1998)—MAMBAC (mean above minus mean below a cut), MAXCOV (maximum covariance), and L-Mode (latent mode factor analysis). MAMBAC (Meehl & Yonce, 1994) requires at least two indicators—an input and an output indicator. The cases are sorted in ascending order on the input and successive cuts[1] are made on this variable at regular intervals. At each cut on the input variable, the mean of cases falling above the cut on the output variable is subtracted from the mean of cases falling below the cut. This difference, designated as $d(x)$, is computed at each successive cut, and as the cut is moved along the input variable, $d(x)$ is plotted on the y-axis against the successive cuts on the x-axis. Taxonic latent structures should produce single-peaked $d(x)$ function with a characteristic peaking near the *hitmax*—the region that provides the clearest separation of putative subclasses. Dimensional latent structures are indicated by a "concave up" shape or the absence of clear peaks. Each of the indicator variables is designated as an

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[1] Taxometric cuts and windows are varied between 100 and 2,000 to ensure enough cuts or windows to detect a small base rate taxon. Increasing the number of cuts to 2,000 did not appreciably change taxometric results.
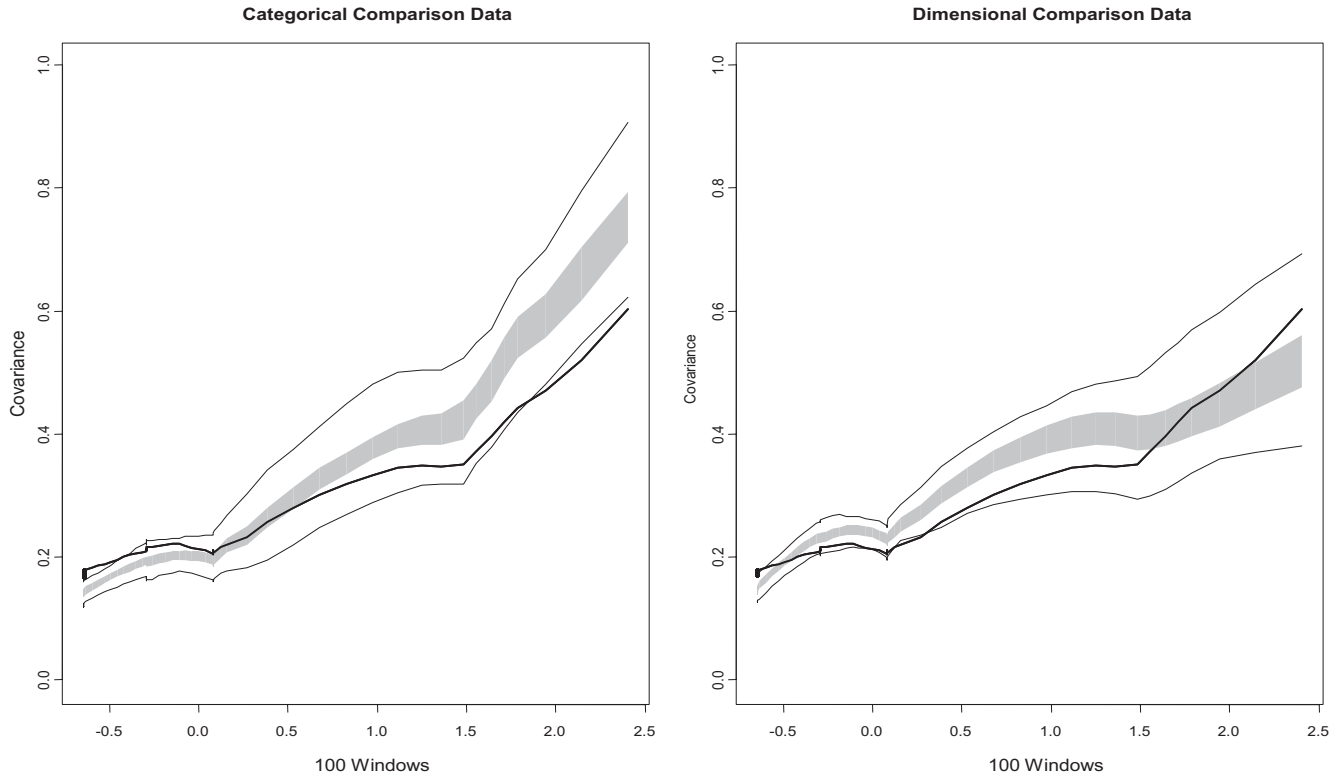
Categorical Comparison Data   **Dimensional Comparison Data**

Figure 2.   Average MAXCOV curve for the ONS data juxtaposed over categorical and dimensional simulations.

input and an output in subsequent analysis. This allows evaluating the graphical outputs for consistency, and when there are more than two indicators, many permutations of input–output pairs can be evaluated. Alternatively, MAMBAC can be conducted with summed input indicators—a process that involves summing all indicators, except the output indicator, into a single composite input indicator and designating cuts on this composite variable while computing $d(x)$ on the output. The aforementioned alternative to the all-pairs method is useful when variables have short lengths.

The MAXCOV analysis (Meehl & Yonce, 1996) requires three or more indicators. MAXCOV selects indicator triplets, one of which is designated as an input indicator, whereas the remaining two indicators are designated as output indicators. After cases are sorted in ascending order on the input, MAXCOV creates successive cuts on this variable. The cuts create intervals of subsamples as cuts move progressively across the entire sample. At each interval, the covariance between the remaining two indicators is computed. MAXCOV computes a conditional covariance function that depicts the covariance on the y-axis against the cut on the indicator on the x-axis. According to Meehl and Yonce (1996), taxonic situations produce conditional covariance functions that are "concave down" or "humped" near the hitmax point. Several MAXCOV plots are produced when indicators are reassigned input–output roles in the analysis.[2]

L-Mode (Waller & Meehl, 1998) is also implemented with at least three indicators. L-Mode factor analyzes the indicator variables and computes factor scores for individual cases using a

one-factor latent variable model. To distinguish between taxonic and dimensional latent structure, L-Mode depicts the distribution of factor scores graphically. Taxonic situations typically yield a bimodal distribution of factor scores with the location of the right (upper) mode and the left (lower) mode corresponding to the relative mixing proportions of the taxon versus complement groups. In contrast, dimensional data yields a unimodal distribution of factor scores.

Consistency tests.   The interpretation of taxometric results is traditionally supported with a number of consistency tests—procedures implemented as part of taxometrics that allow the consistency of the results to be evaluated (Meehl, 1995; Meehl & Yonce, 1994, 1996; Waller & Meehl, 1998). Confidence in taxometric results is increased when there is consistency across multiple taxometric procedures—*multiple hurdles consistency testing*. Within taxometric procedures that generate several curves such as MAMBAC, MAXCOV, and Maximum Eigenvalue (MAXEIG), the consistency of individual curves in support of a structural solution also increases confidence in taxometric conclusions.

We implemented the *case removal consistency test* (Meehl & Yonce, 1994)—a procedure that allows the researcher to evaluate whether taxometric curves change in a predicted pattern following

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[2] We also implemented MAXEIG, the multivariate extension of MAXCOV. As is often the case (Ruscio et al., 2010), the results of MAXEIG were highly redundant with those of MAXCOV. We report only MAXCOV results in this report, but MAXEIG results are available from the corresponding author.

a targeted removal of subsamples of cases from the data. We successively increased the base rate of schizotypal PD in both samples to .10, .20, and .50 by randomly removing complement group members. If high-end peaks on taxometric curves indicate a small base rate taxon, then removal of cases at the low end of the distribution should shift the peaks leftward and the base rate estimate should increase. In contrast, if high-end peaks are due to skewed indicators of a latent dimension, removal of cases at the low end of the distribution should have no impact on the location of the peaks nor should it increase the base rate estimate.

Sample-specific simulations. Sample-specific characteristics, such as indicator skew, mixing proportions, nuisance covariance, and group separations, can influence the shape of taxometric curves (Meehl & Yonce, 1994, 1996; Ruscio, Ruscio, & Meron, 2007). Severe violations of statistical assumptions can make it difficult to visually distinguish between curves produced by taxonic and dimensional data (e.g., Ruscio, Ruscio, & Keane, 2004). We therefore interpreted taxometric curves by comparing them with curves produced by sample-specific simulations of taxonic and dimensional comparison data. The comparison data are sample specific in that they match the distributional characteristics of the research data, including sample size, skew, kurtosis, and expected correlations (Ruscio, Ruscio, & Meron, 2007). We generated 200 samples of taxonic and dimensional comparison data using Ruscio and Kaczetow's (2008) algorithm. This method also allows us to compute a numerical fit index that provides an objective indicator of the relative fit of the research data to the taxonic versus dimensional comparison data. This CCFI ranges from 0 to 1, with values closer to 0 suggesting a dimensional structure and values close to 1 suggesting a taxonic structure. When values close to .50 are obtained, these are generally interpreted as inconclusive as the estimate is viewed as equally supportive of a taxonic or dimensional structure. CCFIs can be interpreted with dual thresholds, such as designating values falling between .45 and .55 as providing equal support for both latent structures and inconclusive. Large-scale Monte Carlo studies support the accuracy of CCFIs at distinguishing between taxonic and dimensional data in taxometric analysis (Ruscio, 2007b; Ruscio & Marcus, 2007; Ruscio, Walters, Marcus, & Kaczetow, 2010). For example, Ruscio and colleagues demonstrated that when MAMBAC, MAXEIG (or MAXCOV), and L-Mode CCFI estimates were combined by computing their mean or seeking consensus, and the .45/.55 dual threshold was used to exclude samples with indeterminate latent structure, accuracy rates exceeded 99% (Ruscio, Walters et al., 2010). We ran taxometric analyses in the R programming environment (R Core Team, 2012) using programs written by Ruscio (2010).

Latent Variable Mixture Modeling

We also submitted item-level variables from both surveys to latent class analysis and factor mixture analysis—to serve as external consistency tests (Schmidt, Joiner, & Kotov, 2004) of the structural solutions obtained from taxometrics. *Latent class analysis* is based on
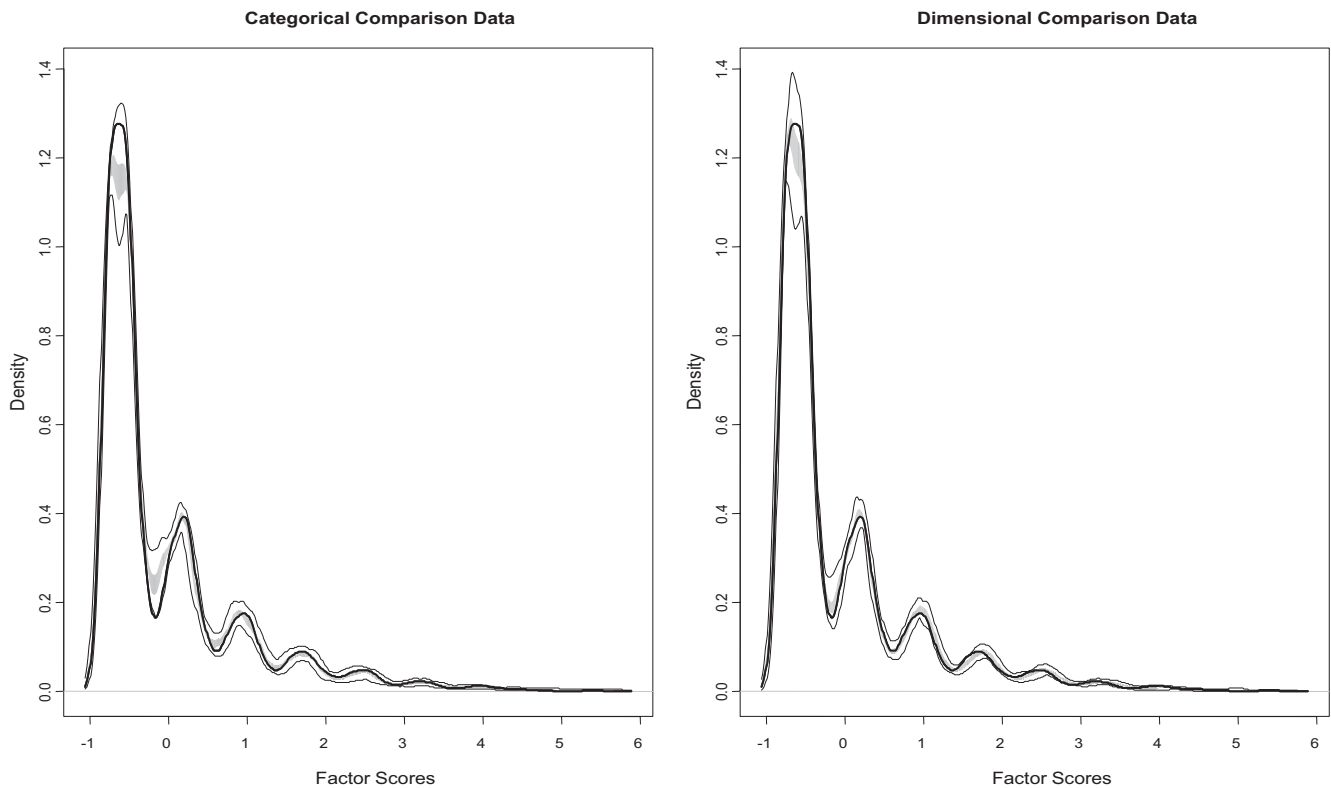

Categorical Comparison Data   **Dimensional Comparison Data**

Figure 3. L-Mode curve generated from the ONS data superimposed on categorical and dimensional simulations.

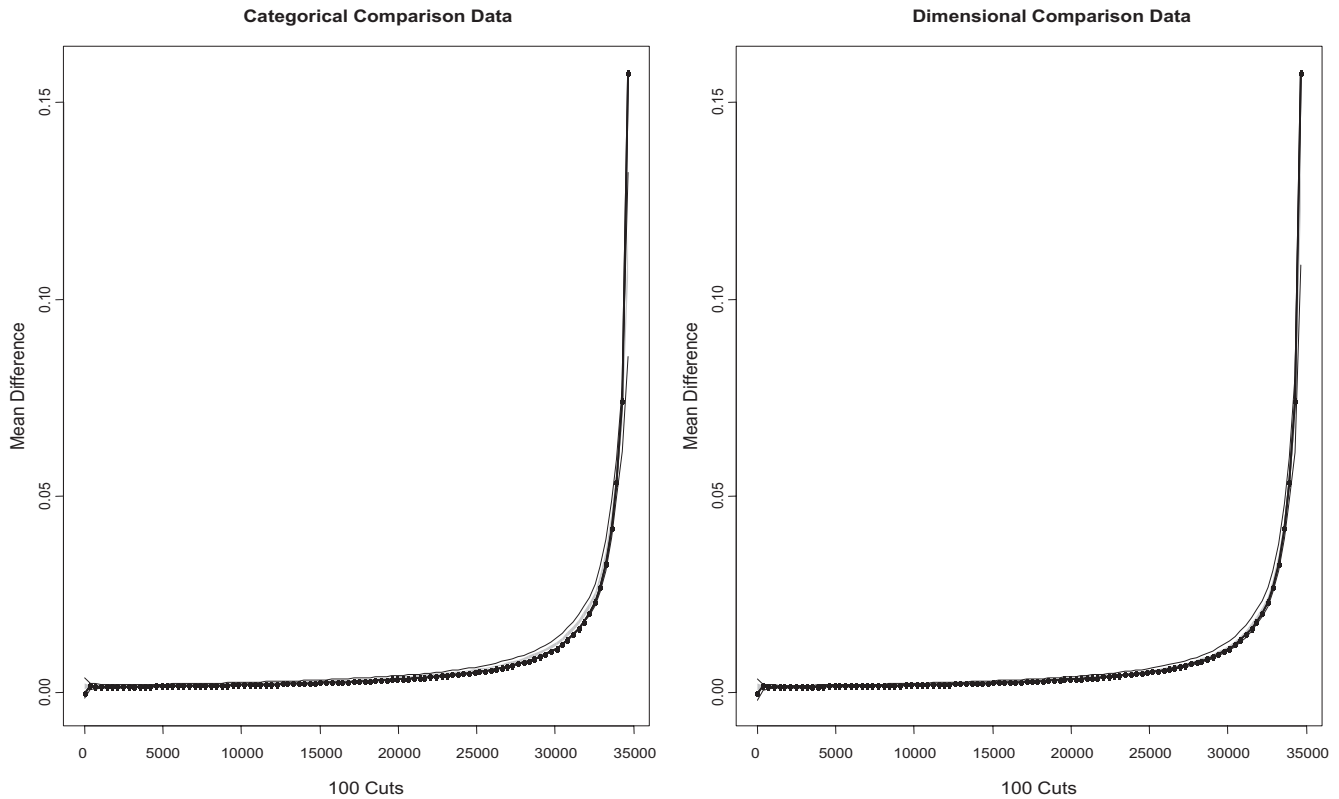**Categorical Comparison Data** **Dimensional Comparison Data**

Figure 4. Averaged MAMBAC curve for the NESARC data superimposed on categorical and dimensional simulations.

the assumption that the relationships among indicator variables are accounted for by a class variable (B. Muthén, 2006, 2008). The removal of the class variable results in null correlations among indicator variables (conditional independence). The number of classes is determined by an evaluation of the patterns of responses, and class membership or assignment is determined by posterior probabilities.

Factor mixture models are a family of latent variable mixture models that combine latent class analysis with the common factor model (Lubke & Muthén, 2005, 2007; B. Muthén, 2006, 2008). The hybrid nature of factor mixture models allows them to represent both categorical and dimensional latent structures (B. Muthén, 2008). Several factor mixture models have been described, all of which vary in their degree of complexity and their analytical configurations—from the simple, highly restrictive, *latent class factor analysis* characterized by measurement invariance and fixed factor variances across classes to more complex models that allow factor covariance matrices to vary across classes (B. Muthén, 2006).

We analyzed item-level variables using latent class analysis and latent class factor analysis implemented with the Mplus 5 program (L. K. Muthén & Muthén, 2008) with robust maximum-likelihood (ML) estimation and an integration algorithm. The Mplus 5 program allows the researcher to evaluate the relative fit of structural solutions in latent class analysis and latent class factor analysis using several fit indices. The fit indices include the traditional log likelihood; information criteria—Akaike information criteria (AIC), Bayesian information criteria (BIC), and sample-size adjusted BIC (aBIC); and likelihood-based statistics—the Vuong-

Lo-Mendell-Rubin (LMR) and the Lo-Mendell-Rubin adjusted likelihood ratio test (aLRT; Lo, Mendell, & Rubin, 2001).

Overall, class solutions with higher log-likelihood values are preferred over solutions with lower values. Class solutions with lower information criteria are preferred over those with higher values. The LMR and aLRT are used to determine the correct structural solution when a dimensional (one-class) structure is nested within a taxonic (two-class) structure; the *p* value would indicate the probability that a dimensional structure produced the data. The hypothesis of a taxonic structure would be rejected in favor of a dimensional structure if the *p* value exceeds the designated alpha level ($\alpha = .05$). To aid the estimation of fit indices, we randomly selected a subsample of 2,000 cases from each epidemiological data and ran mixture models on item-level responses of the selected cases.[3]

Monte Carlo studies have examined the viability of fit indices for elucidating the correct class solution (Lubke & Tueller, 2010; Nylund, Asparouhov, & Muthén, 2007). Of the information criteria, the BIC has been shown to most reliably identify the correct number of class in latent class analysis and factor mixture models compared with the AIC and the aBIC (Nylund et al., 2007). Factor mixture models

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[3] Running the factor mixture models on the full epidemiological samples exceeded the computing power of our computers. We analyzed several random subsamples drawn from the epidemiological samples—the class solutions did not change appreciably.

outperform latent class models at failing to reject simpler $k-1$ models in favor of more complex k models when both are implemented with LMR and aLRT as fit indices. Findings thus suggest that the BIC, LMR, and aLRT, when implemented with factor mixture models, may reasonably prefer one-class models when dimensional structures are compared with categorical models.

Creation of Candidate Schizotypal PD Indicators for Taxometric Analysis

We created candidate indicators for the taxometric analysis by summing item-level variables in each survey into composite indicators. Composite, rather than item-level, variables are preferable because taxometric methods, especially MAMBAC, tend to underperform (e.g., increase risk of pseudotaxonic results), with binary indicators and variables that poorly mimic continuous distributions, such as ordered categorical data or continuous scales with short lengths (Beauchaine, 2003; Ruscio & Walters, 2009). We created the indicators by submitting the survey items to principals components analyses (PCA) with promax rotation and allowing component solutions to guide the summation of items into scales. We selected a three-component solution in both data sets (see Table 1). Our component solutions are consistent with that of studies that support a three-factor structure for schizotypal PD comprising cognitive–perceptual, social–interpersonal, and disorganization dimensions (e.g., Fossati, Raine, Carretta, Leonardi, & Maffei, 2003).

Evaluation of Candidate Schizotypal PD Indicators for Taxometrics

We evaluated the viabilities of the candidate indicators for taxometric analysis. It has been recommended that indicators selected for taxometric analyses separate putative groups by at least 1.25 Cohen's d units (Meehl, 1995; Meehl & Golden, 1982). Meehl and Golden (1982) recommended that nuisance correlation—within-group interindicator correlation—should ideally not exceed .30, as this may, in some cases, attenuate the clarity of taxonic curves, causing them to appear dimensional. Using *DSM–IV* diagnostic status available in both samples to assign cases to putative groups, so that people classified as meeting criteria for schizotypal PD were assigned as putative taxon members, we estimated the indicator validities and nuisance covariance of the indicator pairs in both datasets. Table 2 summarizes the descriptive statistics, indicator validities, nuisance correlation, and full-sample correlations of the indicators. Overall, the indicators in both surveys exceeded requirements for use in taxometric analyses. We submitted the indicator pairs to taxometric analysis, defining class membership based on the *DSM–IV*-based a priori classification. We configured the analyses to generate simulated comparison data (matching the distributional characteristics of the research data but varied by latent structure) using the same a priori classifications to ensure that taxometric procedures were generating identical populations of comparison data.
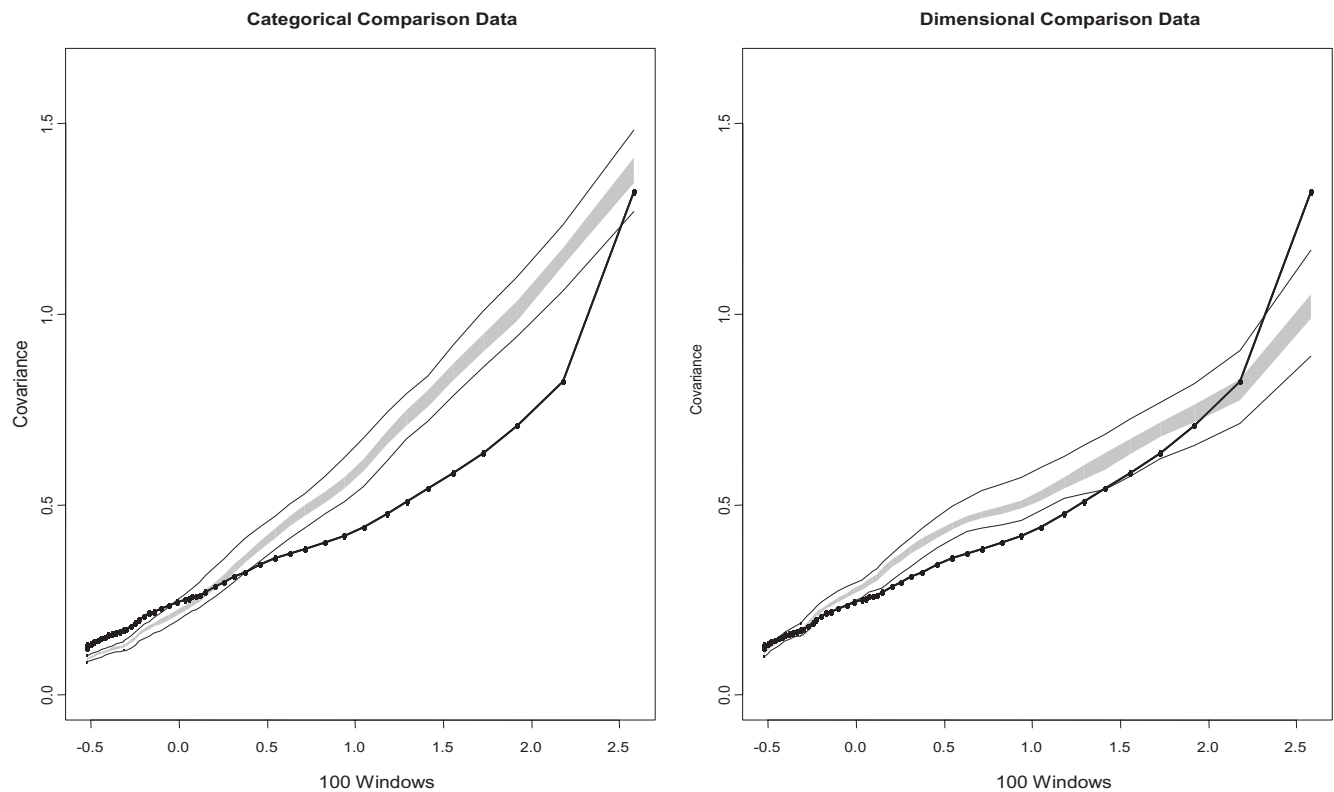

Figure 5. Average MAXCOV curve generated from the NESARC data juxtaposed over categorical and dimensional simulations.

Construct Validation of the Presumptive Latent Structure

We decided a priori to seek further elucidation of the characteristics of taxon group members in the case of a taxonic structure, or the correlates of the latent dimension if taxometrics supported a dimensional structure. The external variables available for such venture differed by the epidemiological survey. In the ONS, the external variables included functional psychosis, cognitive functioning, disability, and treatment seeking. In the NESARC survey, the external variables included a classification of "probable schizophrenia or psychotic illness" since the 2001–2002 NESARC survey, and Social Functioning, Role-Emotional, and Mental Health subscales of the SF-12v2.

Results

Taxometric Analysis of Schizotypal PD in the ONS Survey

Given the length of the scales produced in the ONS data, we implemented MAMBAC with summed input variables. MAMBAC produced three individual curves that appeared to be rising at the high end of the distribution. When the average curve is juxtaposed over curves produced by the simulated taxonic and dimensional comparison data, there appears to be a much better fit with the graphical output produced by the

simulated dimensional data (see Figure 1). Whereas the average curve falls within the area bounding the minimum and maximum values of both the taxonic and dimensional simulations, the research data better overlaps with the gray band representing the middle 50% of data points obtained in the dimensional simulation.

MAXCOV produced three individual curves that were flat for most of the distribution but rising at the high end of the distribution. Figure 2 depicts the average MAXCOV curve generated from the research data superimposed on sample-specific simulations of taxonic and dimensional comparison data. There is a clearer, better fit of the research data to the simulated dimensional comparison data.

The L-Mode curve produced by the research data assumed a multimodal shape, rather than the prototypical bimodal shape expected for taxonic data or the unimodal shape expected for dimensional data (see Figure 3). As noted by Ruscio and Walters (2009), variables that poorly mimic continuous distributions may produce multimodal L-Mode curves. A careful examination of Figure 3 shows that the research data are a better fit with the dimensional simulation.

Consistency Tests

Multiple hurdles consistency testing. All taxometric methods supported a dimensional structure of schizotypal PD in the ONS data through an examination of graphical outputs. We used
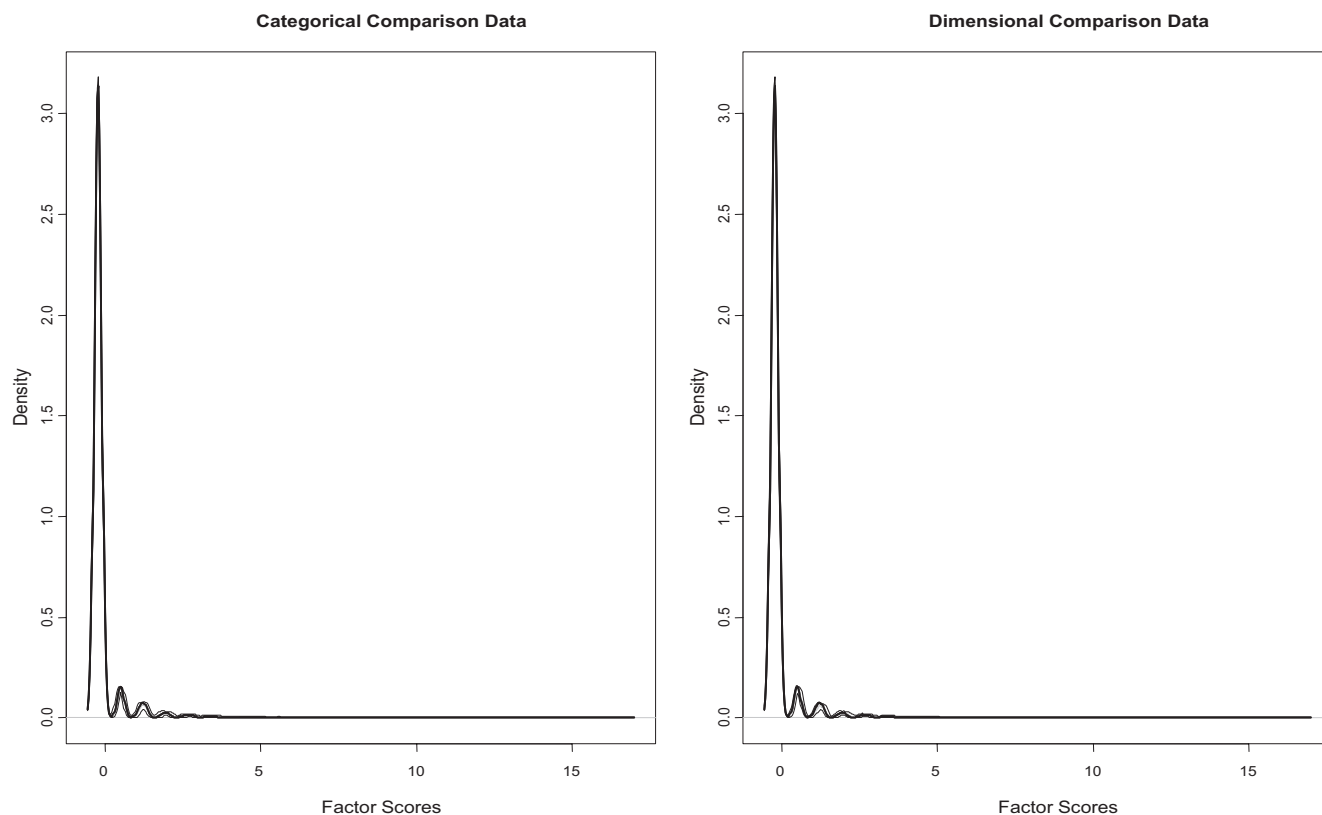

Figure 6. L-Mode curve generated from the NESARC data superimposed on categorical and dimensional simulations.

Table 3
Predictive Validities of Categorical and Dimensional Models

External variables	Dimensional severity scores	Categorical DSM diagnosis	Dependent correlations	Final model R^2	Incremental validity (R^2 change)	Tolerance
ONS survey						
Psychosis	$r = .333^*$	$r_{pb} = 0.284^*$	$Z = 4.81^*$	0.129^*	0.018^*	0.745
Functional psychosis (SCAN)	$r = .116^*$	$r_{pb} = 0.134^*$	$Z = -1.67$	0.021^*	0.008^*	0.745
Norm-based social functioning scale	$r = -0.221^*$	$r_{pb} = -0.145^*$	$Z = -7.16^*$	0.050^*	0.001^*	0.744
Norm-based role-emotional scale	$r = -0.263^*$	$r_{pb} = -0.183^*$	$Z = -7.61^*$	0.072^*	0.003^*	0.744
Norm-based mental health scale	$r = -0.239^*$	$r_{pb} = -0.140^*$	$Z = -9.34^*$	0.058^*	0.001^*	0.745
Intellectual functioning (verbal IQ)	$r = -0.090^*$	$r_{pb} = -0.070^*$	$Z = -1.85$	0.009^*	0.001^*	0.755
Medication, counseling, or therapy	$r = .203^*$	$r_{pb} = 0.182^*$	$Z = 1.98^{**}$	0.050^*	0.008^*	0.745
NESARC						
Probable psychosis	$r = .118^*$	$r_{pb} = 0.096^*$	$Z = 5.08^*$	0.015^*	0.000	0.552
Norm-based social functioning scale	$r = -0.233^*$	$r_{pb} = -0.174^*$	$Z = -13.85^*$	0.055^*	0.001^*	0.552
Norm-based role-emotional scale	$r = -0.197^*$	$r_{pb} = -0.144^*$	$Z = -12.34^*$	0.039^*	0.000	0.552
Norm-based mental health scale	$r = -0.246^*$	$r_{pb} = -0.175^*$	$Z = -16.70^*$	0.061^*	0.000	0.552

Note. DSM = *Diagnostic and Statistical Manual of Mental Disorders*; NESARC = National Epidemiologic Survey on Alcohol and Related Conditions; ONS = Office of National Statistics; r_{pb} = point biserial correlation; SCAN = Schedule for Clinical Assessment in Neuropsychiatry.
* $p < .001$.

the multiple hurdles framework to evaluate the CCFI estimates produced by the taxometric methods by averaging the estimates produced by each method. The estimates were .45, .417, and .293 for MAMBAC, MAXCOV, and L-Mode, respectively. The average CCFI is .386, which falls outside the .45/.55 dual threshold and supports a dimensional model.

Case removal consistency test. Graphical outputs from the case removal consistency test are available from the first author upon request. Removal of cases from the complement group to progressively increase the base rate of the schizotypal PD group did not result in changes in taxometric curves of base rate that would support a taxonic structure.

Table 4
Results of Latent Variable Mixture Modeling of ONS and NESARC Schizotypal PD Data

	LL	K	AIC	BIC	aBIC	LMR	aLRT
ONS LCA							
1-class	−6204.19	11	12430.38	12489.83	12454.89	NA	NA
2-class	−5665.01	23	11376.02	11500.32	11427.25	1078.37 (p = .000)	1066.37 (p = .000)
3-class	**−5540.91**	**35**	**11151.83**	**11340.98**	**11229.79**	**248.19 (p = .000)**	**245.43 (p = .000)**
4-class	−5494.88	47	11083.76	11347.76	11188.45	92.07 (p = .123)	91.045 (p = .125)
5-class	−5475.66	59	11069.31	11388.16	11200.73	38.446 (p = .461)	38.018 (p = .464)
ONS LCFA							
1-factor/1-class	−5633.09	22	11310.18	11429.08	11359.19	NA	NA
2-factor/1-class	−5526.73	23	11099.45	11223.75	11150.68	NA	NA
3-factor/1-class	**−5517.49**	**25**	**11084.98**	**11220.09**	**11140.66**	NA	NA
1-factor/2-class	−5479.86	45	11049.73	11292.92	11149.96	306.457 (p = .000)	304.668 (p = .000)
2-factor/2-class	−5472.37	46	11036.75	11285.34	11139.21	108.70 (p = .147)	108.07 (p = .148)
3-factor/2-class	−6444.56	48	12985.11	13244.52	13092.03	685.47 (p = .997)	681.46 (p = .997)
NESARC LCA							
1-class	−2160.06	16	4352.12	4439.50	4388.67	NA	NA
2-class	−1633.02	33	3332.05	3512.26	3407.43	1054.073 (p = .005)	1040.132 (p = .005)
3-class	**−1548.75**	**50**	**3197.50**	**3470.55**	**3311.71**	**168.55 (p = .009)**	**167.231 (p = .009)**
4-class	−1510.48	67	3154.95	3520.84	3307.99	76.549 (p = .075)	75.951 (p = .077)
5-class	−1490.43	84	3148.86	3607.59	3340.73	40.086 (p = .558)	39.772 (p = .561)
NESARC LCFA							
1-factor/1-class	−1561.64	32	3187.27	3362.03	3260.36	NA	NA
2-factor/1-class	−1555.60	33	3177.19	3357.41	3252.57	NA	NA
3-factor/1-class	**−1531.02**	**35**	**3132.04**	**3323.18**	**3211.98**	NA	NA
1-factor/2-class	−1504.86	65	3139.71	3494.68	3288.18	113.57 (p = .691)	113.11 (p = .692)
2-factor/2-class	−1508.50	65	3146.99	3501.29	3294.79	90.06 (p = 1.000)	89.69 (p = 1.000)
3-factor/2-class	−1491.00	68	3118.43	3489.78	3273.75	4508.45 (p = 1.000)	4409.22 (p = 1.000)

Note. Fit indices were computed on randomly selected subsamples of 2,000 cases from each epidemiological sample to allow the ease of computing of hybrid models. LL = log-likelihood; k = number of free parameters; NA = Not Applicable; LCA = Latent class analysis; LCFA = Latent class factor analysis; AIC = Akaike Information Criteria; BIC = Bayesian Information Criteria; aBIC = Sample-size Adjusted BIC. Bold text represents the favored structural model.

Taxometric Analysis of Schizotypal PD in the NESARC Survey

MAMBAC produced individual curves and an average curve rising at the end of the distribution. In Figure 4, the research curve overlaps with most of the gray band in the dimensional simulation so that the latter is barely visible. In contrast, the gray band in the categorical simulation is visible behind the research curve, suggesting a lesser fit.

MAXCOV produced three individual rising curves and a similarly rising average curve. In Figure 5, the average curve appears to be a slightly closer fit with the simulated dimensional data when it is superimposed on categorical and dimensional simulations.

In Figure 6, there was no clear distinction between the categorical and dimensional simulations, rendering an assessment of latent structure impossible through visual inspection.

Consistency Testing

Multiple hurdles consistency test. MAMBAC and MAX-COV curves obtained from the NESARC data generally supported a dimensional structure. The CCFI estimates obtained from the analyses were .265, .361, and .534 for MAMBAC, MAXCOV, and L-Mode, respectively. The average of these estimates is .387, which falls outside the .45/.55 dual threshold and supports a dimensional structure.

Case removal consistency testing. There were no changes in curve signatures that would support a taxonic structure—curves remain unchanged regardless of the degree of case removal. Further, the changes in base rate estimates in MAMBAC and

MAXCOV were not commensurate with what would be expected for a taxonic structure.

Comparative Validities of a Categorical Versus Dimensional Model

Table 3 summarizes the association between the competing structural models and the external variables in each epidemiological data. The categorical approach is based on *DSM–IV* schizotypal PD diagnosis, and the dimensional structure is based on severity scores obtained by summing individual schizotypal PD items. The correlations between the categorical and dimensional models are high in both the ONS ($r_{pb} = .505$, $p < .001$) and the NESARC ($r_{pb} = .669$, $p < .001$) data. Although the correlations are small, it is clear from Table 3 that the dimensional model generally produces stronger correlations than the categorical model, with often-significant Fisher's z test of the difference between dependent correlations. Further, it is clear from the table that the categorical model does not appear to add strongly to the prediction offered by the latent dimension. The incremental validities of the categorical model achieved statistical significance, but the actual R^2 change produced by their inclusion in prediction models is minimal for predicting each external variable.

Latent Variable Mixture Modeling of Schizotypal PD

Table 4 summarizes the results of latent class analyses and latent class factor analyses of the ONS and NESARC schizotypal PD data. In both data sets, latent class analysis tended to favor
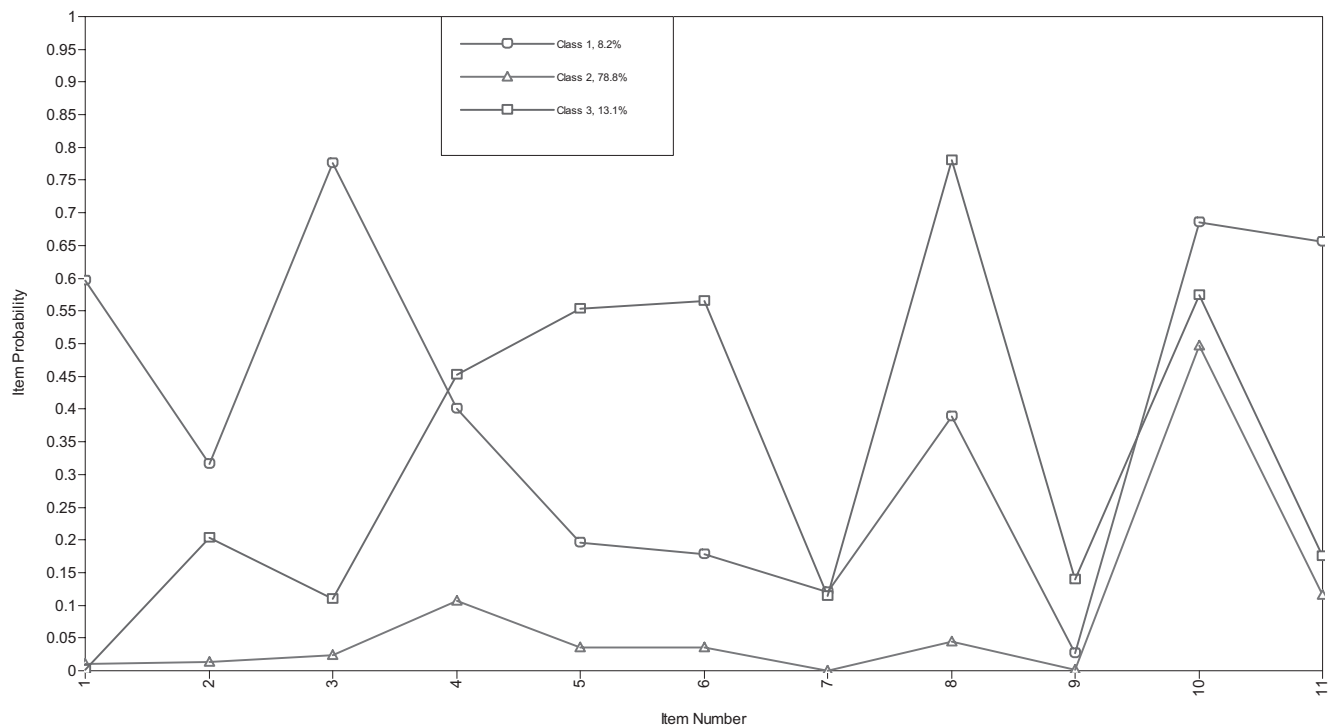

Figure 7. Class probabilities of endorsing items in the ONS data for the three-class latent class model.
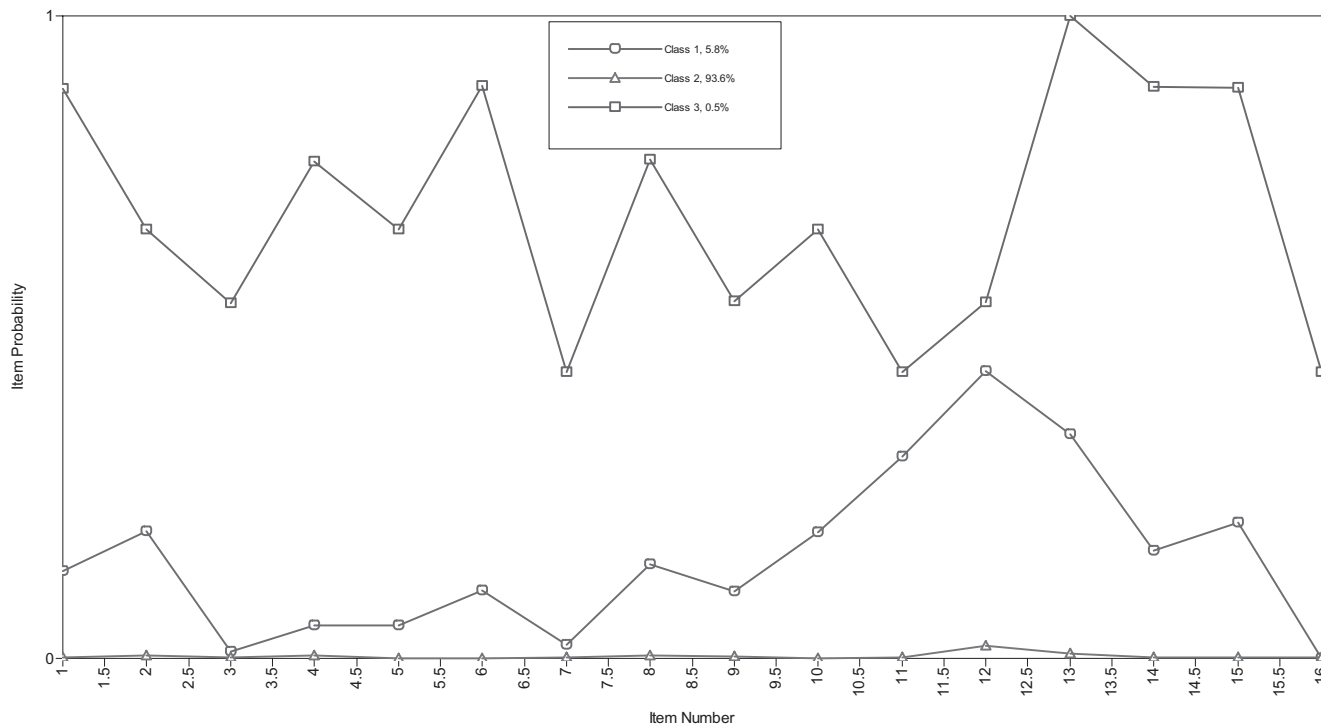
Figure 8. Class probabilities of endorsing items in the NESARC data for the three-class latent class model.

models with larger number of classes when the traditional log likelihood and the AIC are examined. Whereas the aBIC preferred a four-class model, the BIC, LMR, and the aLRT preferred a three-class model in the ONS latent class analysis. Latent class analysis of the NESARC data similarly preferred the three-class solution over other structural models when the BIC, LMR, and the aLRT estimates are interpreted as fit indices. An examination of latent class analysis item profile (Figure 7 and Figure 8) of the three-class solution shows no evidence of qualitative differences across classes in item endorsement patterns. Rather, the odds of endorsing items across classes appear to differ quantitatively.

Latent class factor analysis exercised preference for one-class (dimensional) solutions over two-class structures in both the ONS and NESARC data sets. Whereas the traditional log likelihood and the AIC favored the two-class solution, the BIC, aBIC, the LMR, and the aLRT tended to favor the one-class solution over a two-class structure. The best-fitting structure in both data sets was the three-factor/one-class solution, which produced the lowest information criteria estimates. This solution was also supported by *p* values generated by the LMR and aLRT three-factor/two-class structure, which suggested a .997 probability that the three-factor/one-class structure produced the ONS data and a 1.00 probability that a three-factor/one-class model produced the NESARC data. Figure 9 and Figure 10 depict the item profiles for the three-factor/two-class models both of which suggest severity rather than qualitative class differences. Across mixture models, we obtained the lowest (best) BIC value for the three-factor/one-class model in both data sets.

Discussion

Overall, the results of the taxometric and latent variable mixture models provided greater support for a dimensional, rather than a taxonic, structure for schizotypal PD, indicating the absence of a latent boundary that distinguishes people with schizotypal PD from the rest of the population. The latent dimension outperformed *DSM–IV* schizotypal PD status at predicting psychosis, disability, intellectual functioning, and treatment history; thus, we have an unsurprising state of affairs—regardless of latent structure, dimensional measures are usually more powerful predictors of external variables than categorical predictors (Grove, 1991a). Further, a plausible taxonic predictor (schizotypal PD status) did not contribute substantially to the prediction of the external variables over and above the latent dimension. Although not a test of latent structure, it may be argued that the failure of a plausible taxonic predictor to contribute substantial information over and above the latent dimension indicates that a solely dimensional model is adequate to predict the aforementioned correlates of schizotypal PD and may be sufficient to explain the phenomenology of schizotypal PD.

The dimensionality of schizotypal PD speaks to its organization in diagnostic systems. The recent appeals to reorganize personality disorders along broad personality dimensions have included schizotypal PD and other Cluster A PDs (Chmielewski & Watson, 2008; Tackett, Silberschmidt, Krueger, & Sponheim, 2008). Indeed, taxometric evidence has generally supported the dimensional structure of PDs, lending empirical support to such a move for most personality disorders. If the goal of nosological systems is to reflect empirical reality, a purely dimensional model may adequately describe schizotypal PD. In addition, the currently pub-
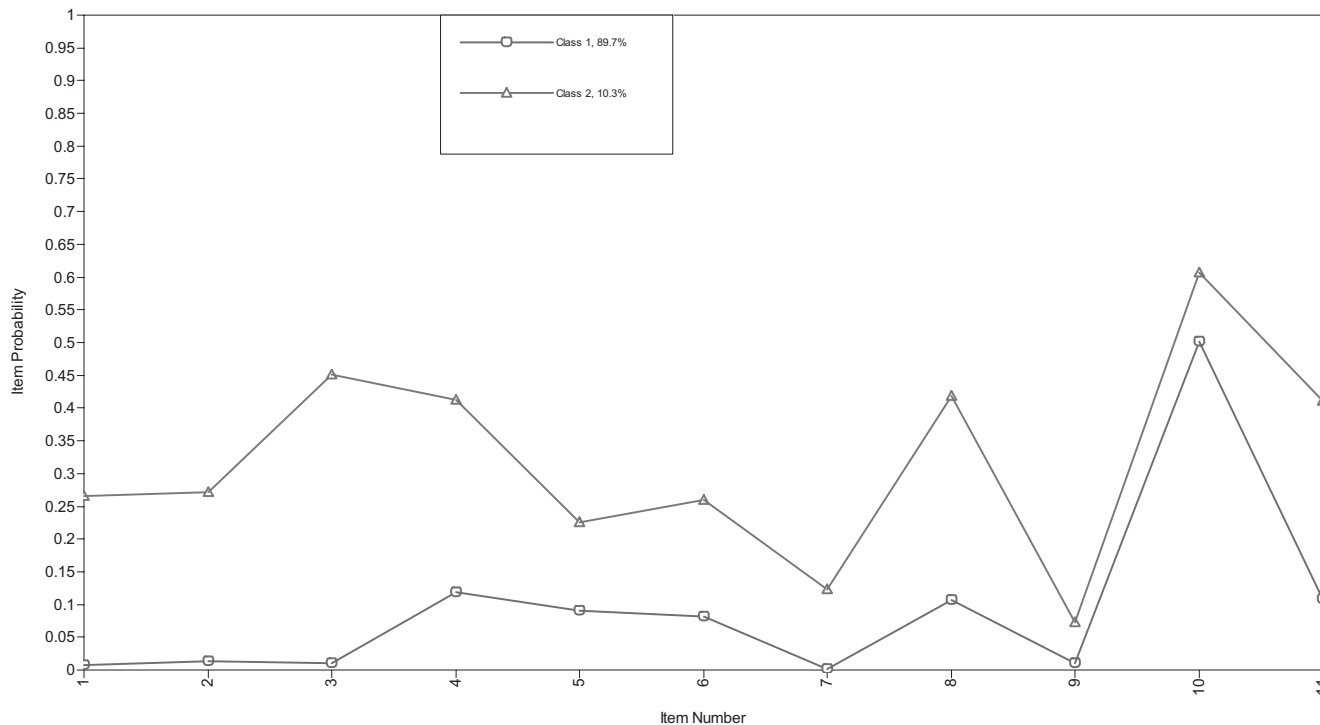
Figure 9.   Item profiles for the three-factor/two-class model for schizotypal PD in the ONS data.

lished taxometric studies support a dimensional structure for paranoid and schizoid PD (Ahmed et al., 2012; Edens, Marcus, & Morey, 2009).

The dimensionality of phenotypes describing Cluster A disorders is consistent with Eysenck's (1993) and Claridge's (2006) fully dimensional model, in which a dimensional distribution of schizotypy is expressed as a continuum of expression ranging from predisposing traits to schizophrenia (see also, Claridge & Beech, 1995). It is also possible that schizotypy is expressed as taxonic and dimensional entities that include dimensional Cluster A PD constructs and other schizophrenia phenotypes that are taxonic. Perhaps at lower gradients of expressivity, schizotypy is expressed as dimensional entities, but as multiple risk factors accumulate beyond a threshold, qualitatively distinct entities emerge, which is in concert with Gottesman and Shield's (1972) model.

It appears that our findings regarding the latent structure of schizotypal PD run contrary to what may be expected as an implication of Meehl's (1962, 1989, 1990) theory. It should be noted, however, that criterial symptoms of schizotypal PD neither map strongly onto positive and negative schizotypy nor adequately capture social anhedonia or other aspects of schizotypy. Studies that have demonstrated the taxonicity of schizotypy have drawn indicators from several modalities that include psychometric scales, neurophysiological indices, neurocognitive measures, and other intermediate phenotypes (e.g., Lenzenweger & Korfine, 1992; Lenzenweger, McLachlan, & Rubin, 2007; Linscott, 2007). Further, it is remarkable that our results run contrary to Tyrka and colleagues' (1995) taxometric study of schizotypal PD, in which they used indicators—social withdrawal, social anxiety, passivity, flat affect, peculiarity, and poor prognosis—that they viewed as

analogous to schizotypy in a sample that included high-risk individuals. It may be that the disparity in the latent structure of criterial schizotypal PD (reflected in our study) and schizotypy-linked schizotypal PD (Tyrka et al.), and, of course, schizotypy, very well underscores the nonisomorphic nature of schizotypal PD and schizotypy.

Methodological differences between our study and the Tyrka et al. (1995) study could also account for differences in latent structure findings. Tyrka and colleagues analyzed data obtained from an admixed sample that comprised individuals born to women who had schizophrenia (classified as high risk) and individuals born to mothers without a psychiatric diagnosis (low risk), matched by age, social class, sex, and residence. The sampling strategy allows the latent composition of the putative taxon to be increased to a region in which it is easily detectable. In contrast, we analyzed population-based data rather than selected samples. The use of admixed samples has been challenged by several taxometric authorities, as it increases the risk for obtaining spurious taxa (e.g., Grove, 1991b; Schmidt et al., 2004). Combining "high-risk" individuals with a control sample may create artificial discontinuities between both groups on schizotypal PD indicators. It may be more appropriate to sample individuals of varying levels of risk—for example, individuals with an affected parent, sibling, or extended family member—to allow the spectrum of risk to be assessed.

Our results engender further questions about the latent structure of schizophrenia risk and the schizophrenia spectrum. Taxonic findings for certain schizophrenia phenotypes, such as negative symptoms (Blanchard et al., 2005), suggest that the schizophrenia spectrum is at least underpinned by discontinuous entities, but direct tests of diagnostic boundaries are required to answer this
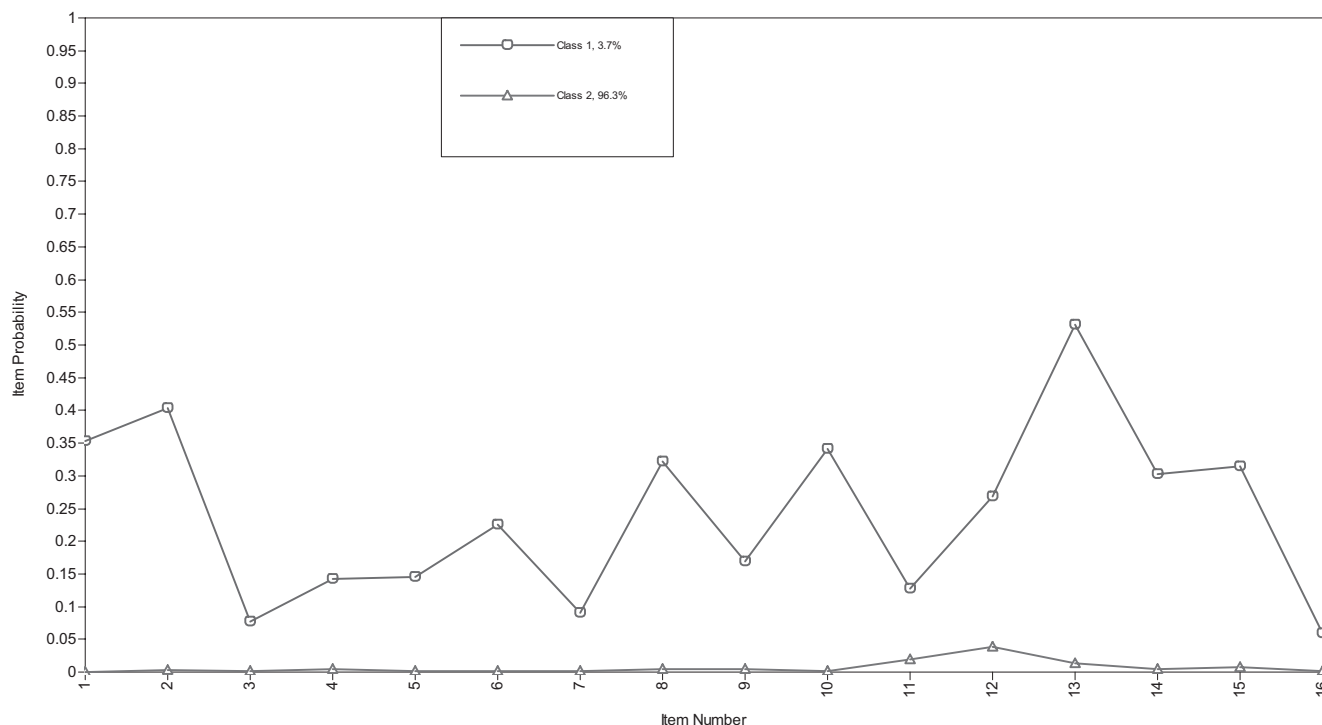
Figure 10. Item profiles for the three-factor/two-class model for the schizotypal PD NESARC data.

definitively. Such boundaries would likely coexist with a dimensional distribution of some features or expressions of schizotypy, such as hypohedonia (Linscott, 2007), magical ideation (Horan et al., 2004; Meyer & Keller, 2001), and psychotic experiences (Ahmed, Buckley, & Mabe, 2012). It is possible that the latent structure of schizotypy is a hybrid/pluralist one—comprising both taxonic and dimensional aspects that contribute to a similarly complex system of phenotypic expression that comprises taxonic and dimensional phenotypes.

The current study has several strengths. These include its use of large population-based samples, its use of empirically supported consistency tests within a taxometric framework, its implementation of a construct validation procedure of latent structure, and its incorporation of latent variable mixture modeling. Taxometric and mixture models similarly converged on a dimensional structure. There are, however, a number of limitations. Interview items in both surveys focused on assessing *DSM* criteria, and these items served as the only source of indicators used in the study. Our findings would have been more defensible had we combined indicators from interviews with psychometric measures, neurocognitive performance, neurophysiological indices, and other endophenotypes associated with schizotypal PD (e.g., eye-tracking dysfunction). These were, of course, unavailable in the survey. Another limitation concerns the measure of schizotypal PD in the NESARC survey—the AUDADIS-IV, a measure that has not been extensively evaluated with regard to its association with traditional, clinician-administered measures such as the SCID-II. Although the validity of the results of the NESARC data may hinge on the validity of the AUDADIS-IV as a measure of schizotypal PD symptoms, the convergence of NESARC results with the ONS, which used the SCID-II, instills some confidence in the study results.

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