

Consistency and Change in Idiographic Personality: A Longitudinal ESM Network Study

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Open materials on GitHub (<https://github.com/emoriebeck/Idiographic-Network-Consistency>) and the Open Science Framework (<https://osf.io/fyxza/>) contain raw data files, results, and code used to conduct the analyses in this manuscript as well as a number of additional analyses referenced in footnotes in the manuscript. A web application (https://emoriebeck.shinyapps.io/pairs_graphicalvar/) contains visualizations of the more than 700 networks constructed in the analyses.

Abstract

The study of personality development primarily focuses on between-person, nomothetic assessments of personality using assessments of personality traits. An alternative approach uses individual, idiographic personality assessment, defining personality in reference to one's self rather than to others. Nomothetic approaches to personality development identify high levels of consistency in personality, even over decades. But the developmental pattern of idiographic personality is unclear, partially due to difficulties in assessing personality idiographically. We examine a number of traditional and novel idiographic modeling techniques using two years of ESM data from the Personality and Interpersonal Roles Study (PAIRS; $N = 372$ participants, total assessments $N = 17,715$). We computed idiographic lagged (lag 1 autoregressive) and contemporaneous (concurrent) graphical VAR models, as well as several other idiographic models, for each subject at the individual level at both waves, which are represented as networks. The utility and interpretation of these newer idiographic personality models at an individual level is demonstrated by using two example subjects. Across all participants, idiographic personality models were heterogeneous in structure, indicating the value of an idiographic approach. Contemporaneous, but not lagged, idiographic models were consistent over time. Despite normative levels of consistency, both types of idiographic models exhibited a great range of individual differences in consistency where some people were completely stable across two years whereas others were very unlike their former selves. In sum, we demonstrate that novel idiographic modeling techniques provide a useful tool to address questions of personality dynamics that were not possible with more traditional idiographic assessments.

Keywords: personality, development, idiographic, longitudinal, networks

Consistency and Change in Idiographic Personality: A Longitudinal ESM Network Study

Personality is characterized by both continuity and change (Roberts & Mroczek, 2007). Typically, continuity and change are assessed using three distinct metrics. Across long periods of time, many personality traits exhibit high levels of rank-order consistency (Hopwood et al., 2013; Roberts & DelVecchio, 2000; Specht, Egloff, & Schmukle, 2011; Terracciano, Costa Jr, & McCrae, 2006). Despite this consistency, mean-level (i.e. normative) changes occur throughout the lifespan (Costa & McCrae, 2002; Roberts, Walton, & Viechtbauer, 2006; Robins, Fraley, Roberts, & Trzesniewski, 2001; Soto & John, 2012). However, among these normative patterns are considerable individual differences in the direction and rate of change (Mroczek & Spiro, 2003; Roberts & Mroczek, 2008). These three types of patterns – consistency, mean-level change, and individual differences in change – are the most studied types of personality development. Common among all three is a between-person, nomothetic assessment of personality.

With the exception of studies of ipsative change that test the consistency of profiles of personality traits within a person over time (e.g., Block, 1971; De Fruyt et al., 2006; Roberts et al., 2006; Roberts, Caspi, & Moffitt, 2001), few studies take an individual, idiographic approach to personality development where the assessment of personality is based on within-person associations (though see Jackson, Lord, Strube, & Harms, 2019). Idiographic techniques (where the sample size is one person or $N = 1$) refer to methods used for measuring and modeling individuals where the individual is considered *only* relative to him or herself – that is, where personality is defined as the ordering of variables within a person rather than the ordering of people across a single trait dimension. Idiographic assessments of personality are important to consider in regard to development because idiographic continuity and change operates separately from between person assessments of development (Cattell, 1957; Molenaar, 2004). Despite

idiographic assessments being discussed nearly a century ago (Allport, 1937), idiographic assessments of personality development are rarely conducted. Recent technological advances make it both possible and relatively easy to collect idiographic personality data that is suitable for the use of $N = 1$ statistical techniques that have gained prominence in other fields, like clinical psychology (e.g. Beltz, Wright, Sprauge, & Molenaar, 2016; Rodebaugh et al., 2018; Wright et al., 2018) and the study of emotion (e.g. Krone et al., 2017). Despite this, these statistical techniques, which utilize vector autoregression in time series, have not been used within personality psychology to test questions of personality development.

The present paper extends previous developmental idiographic work by using a longitudinal Experience Sampling Method (ESM) to investigate the structure and consistency of idiographic personality across a two-year period. The new idiographic methods allow us to incorporate both within- and across-time patterns directly into the model and to examine indicators directly, not reducing the dimensionality of the data. As a result, we are able to address novel questions concerning the consistency of personality across time.

Idiographic Personality Assessment

Broad nomothetic measures parsimoniously describe the structure of between-person individual differences, but some researchers continue to call for more idiographic approaches that bring the person back into the study of psychology and personality processes (Beltz et al., 2016; Cervone, 2005; Conner, Tennen, Fleeson, & Feldman Barrett, 2009; Fisher, 2015; Grice, 2004; Molenaar, 2004). In their view, broad measures of personality miss important information that explains and describes an individual's unique components of personality. Allport (1937) famously called for an idiographic, person-centered approach to provide insight into personality processes and to account for different structures of personality at the individual level (in addition to, not opposed to, a nomothetic approach; see Beck & Jackson, 2019a). In the present paper,

when we refer to idiographic assessment, we refer to assessments of individuals that assess the structure or manifestations of an individual's personality only relative to themselves.¹ Even though there have been continued calls for idiographic assessment, idiographic personality assessment is rarely conducted.

Much of the early work on idiographic personality assessment hinged on the observation that nomothetic assessments averaged over important sources of variability, both in the temporal manifestations of personality and the contexts in which those manifestations arise (Beck & Jackson, 2019a). This led to two distinct research paths, one of which examined the personality trait structure at the level of the individual using repeated assessments (Block, 1971; Cattell, 1957) and one that specifically targeted interactionism between personality and situation factors (e.g. Bandura, 1977; Endler & Hunt, 1969; Shoda, Mischel, & Wright, 1994; Wright & Mischel, 1987).

The first approach modeled the structure of a single individual's personality using methods similar to those that were used to test the structure of between-person differences using nomothetic assessments. Called P-technique (Cattell, 1957), such methods used factor analytic methods to investigate the organization of personality traits within a person. Within-person investigations are vital to understanding personality, in part because of an assumption that a between-person structure should replicate within individuals (Borsboom et al., 2003). In a notable demonstration (Nesselroade & Molenaar, 2001), only one-third of the sample showed a structure similar to the between person, population estimate. For the remaining two-thirds, an alternative structure of personality was needed. Similarly, Grice (2004) examined how well nomothetic measures of the Big 5 could capture idiographically derived personal constructs and

¹ When we reference idiographic modeling, we refer to statistical techniques (inferential or descriptive) that model the structure or patterns of a single individual's personality that can stand alone and in no way rely on the collection or presence of data on other individuals.

found that at least half of the variability in individual differences relied on the idiographic personal constructs. Studies such as these suggest that understanding personality requires identifying the structure of manifestations of personality at the level of a person, not a population. Despite this, there were few empirical investigations using P-technique throughout the latter half of the century, largely because P-technique requires a large number of repeated measures from an individual, which are difficult to obtain compared to a large number of people.

The second approach to idiographic personality assessment, a contextualist perspective, argued that personality is best understood by embedding personality within a situation or context (Wright & Mischel, 1987). Personality manifestations should be considered in the context of three probabilistic relationships – the probability of a behavior, $p(B)$, the probability of a behavior in a specific context, $p(B|C)$, and the probability of the evoking context, $p(C)$ – all of which may differ from person to person (Wright & Mischel, 1987; Wright et al., 1999; Wright & Zakriski, 2003). Focusing on average levels of behaviors as nomothetic traits do, $p(B)$, overlooks person-specific contingencies that are best thought of as idiographic in nature. For example, children being treated for behavioral disorders at a summer camp were observed by multiple individuals who rated them on a number of dimensions across different contexts (Mischel & Shoda, 1995; Shoda et al., 1994). These studies demonstrated that children who exhibited similar mean-level, nomothetically assessed aggressive behaviors frequently had meaningfully different patterns of psychological precursors, such that some children were aggressive when threatened by peers but not when confronted by authoritative adults, while others showed the opposite pattern. As with P-technique factor analysis, these studies suggest that nomothetic personality differs from idiographic.

However, although the contextualist study of idiographic personality utilized some repeated measures data, these data were largely modeled and understood as averages of levels of

behaviors in pre-defined contexts, not as true probabilistic models of the probabilities of different personality manifestations in given psychological and objective contexts. In other words, the temporal dimension of the data that can answer questions about *sequences* of behavioral or psychological patterns and contexts was ignored in favor of understanding average levels of behavioral or psychological phenomena. To early personality scientists, such questions of timing were of both interest and importance. Cattell (1957) wrote elegantly on the ways in which personality varies over time, arguing that the periodicity of personality manifestations was crucial to understanding fluctuations in personality. However, computational techniques at the time were largely unable to address questions of periodicity in personality.

But emerging technology has made it easier to extend and connect structural, contextual, and time-series lines of inquiry into idiographic assessment and modeling by collecting repeated assessments of individuals in the context of their lives and using emerging statistical techniques for understanding time series data. Experience Sampling (or ambulatory assessment or ecological momentary assessment; Csikszentmihalyi & Larson, 2014), asks individuals to respond to surveys on several occasions across days to weeks. Although ESM data is typically not collected with the intention to be used in idiographic analysis, it is a critical development in the future of idiographic assessment and modeling (Conner et al., 2009). Despite the upsurge in collection of ESM data, there has not been a corresponding increase in using idiographic approaches, like P-technique factor analysis. Instead, the bulk of collected ESM data have been analyzed using multi-level modeling to examine within-person effects and patterns of personality manifestations. A key feature of idiographic modeling is that a person is assessed only relative to him or herself. As such, models that use population-level patterns to inform individual level patterns (so-called “idiothetic” models), like growth models within a MLM framework, are *not* idiographic in the same way Allport (1937) discussed.

The methods implemented in the current paper improve upon both P-technique and contextualist methods by (1) incorporating within- and across-time patterns directly into the model, (2) not reducing the dimensionality of the data in ways that make idiographic models difficult to compare, and (3) probabilistically modeling contextualist relationships among variables. We demonstrate this using both a novel modeling approach as well by demonstrating the longitudinal consistency of these approaches using a longitudinal ESM study.

Advantages of idiographic assessment.

Why use idiographic assessment if it can only answer questions about individuals? Proponents of idiographic approaches argue for at least three advantages relative to between-person, nomothetic approaches. First, as mentioned above, there is evidence to suggest that the between-person (population-level) trait structure may not exist for any particular individual. Idiographic principal components analyses (Borkenau & Ostendorpf, 1998) and factor analyses (Molenaar, 2004) of intensive repeated measures data yield solutions ranging from two and eight factors for individuals rather than the expected Big Five. Even for those individuals with five-factor solutions, the weights of the loadings, the measurement error variances, and the time-series models differed from the between-person Big Five structure (Molenaar, 2004). Further, there is evidence that between-person models do not demonstrate measurement invariance at the individual level (Möttus et al., 2016). Thus, using only the typical Big 5 structure of personality misses “intrinsic unique” individual differences in the configuration and variability of traits that can be discovered when the focus is an individual level of analysis (Cattell, 1957).

Second, idiographic approaches can better account for different manifestations of a broad personality trait. Consider, for example, two individuals who have identical levels of Conscientiousness on a nomothetic personality scale. Although both would be expected to be, on average, equally Conscientious, the manifestations may differ both in time and form (i.e. the

“same” trait may manifest differently across people; Nesselroade & Molenaar, 2016).

Traditionally, from a nomothetic view, this has been approached by examining lower-order personality characteristics, such as facets (Jackson et al., 2009; Soto, 2012), aspects (DeYoung, Carey, Krueger, & Ross, 2016), or items (Möttus, Kandler, Bleidorn, Riemann & McCrae, 2017; Möttus, 2016; Wood, Nye, & Saucier, 2010). But this still misses unique associations *between* lower-order personality characteristics, such as whether an individual’s sociability (a facet of Extraversion) is related their interpersonal warmth (a facet of Agreeableness). Allowing for dependencies across lower-and higher-order personality characteristics thus provides a better snapshot of an individual’s personality that is not assessed in traditional assessments.

Third, as we define it herein, idiographic data are inherently temporal given that they require multiple responses from a single individual (through, for example, ESM). As a result, idiographic models are able to better examine the effects of context and time and to examine so called *if...then* contingent patterns ($p(B|C)$) that are a hallmark of contextualized idiographic assessment (Wright & Mischel, 1987; Mischel & Shoda, 1995). For example, compared to traditional models of personality, idiographic models incorporate multiple different situations due to repeated responses. As such, situations can be directly incorporated into the same model. In contrast, more traditional approaches must statistically interact separate personality and situation terms (e.g. Sherman, Rauthmann, Serfass, & Jones, 2015), which may miss idiosyncratic patterns of person-situation transactions.

Personality Development

An idiographic approach offers the opportunity address existing gaps in research into personality development. Notably, this approach addresses whether people’s personality structures are consistent across time. Typically, personality development examines rank-order or mean-level change, both of which are variable-centered measures, rather than individual /

person-centered measures. More rarely, personality development considers ipsative change, which gets closer to individual-level change by examining personality profiles across time (Roberts, Wood, & Caspi, 2008). Relative to other measures, like mean-level and rank-order consistency, ipsative consistency has received a less attention in the assessment of personality consistency. Rather than assessing population-level patterns of change in single metrics of personality (e.g. mean-level change in Extraversion), ipsative consistency indexes the within-person patterns of change across metrics over time. Thus, ipsative consistency is distinct from other measure of consistency both by assessing patterns of change and doing so within a person. Studies of ipsative consistency of personality throughout the lifespan indicate that, on average, ipsative consistency of personality traits tends to be quite high over the lifespan on average, but there are individual differences in ipsative change (Asendorpf & van Aken, 1991; Block, 1971; De Fruyt et al., 2006; Donnellan et al., 2011; Robins et al., 2001). These individual differences in change indicate the utility of assessing personality within a person rather than solely between-person, as not everyone changes alike.

Almost all studies of ipsative consistency of personality to date have examined the ipsative consistency of nomothetic measures of personality, and almost no work has examined the longitudinal consistency of contextualized, idiographic personality assessments. That is, the previous studies of ipsative consistency presume that the factor structure is similar for each person in contrast to idiographic assessments which has no such assumption. Even those studies that claim to test the profile (ipsative) consistency of contextualized idiographic personality assessments (Fournier, Moskowitz, & Zuroff, 2008; Shoda, Mischel, & Wright, 1994) test only short-term consistency (weeks), rather than longitudinal consistency (months to years). Given that short-term consistency might reflect more about the consistency of the situation rather than the consistency of personality, it is currently unclear whether there is longitudinal consistency in

the profile of an individuals' contextualized personality assessments. Moreover, it is unknown if there are individual differences in consistency, indicating that some people are more or less stable than others. While there are individual differences in ipsative personality consistency, it is unknown whether idiographic personality is consistent. Previous theorists have argued that much of personality structure is based on situations (Mischel, 1968), which if true, could lead to very low estimates of constancy and few, if any, individual differences. Finally, it is unclear whether individual differences in consistency (if found) relate to important outcomes, similar to how changes in nomothetic measures of personality do.

Idiographic Personality Assessment Models

There are a number of methods for assessing idiographic personality, including P-technique factor analysis (Cattell, 1947, 1957; Molenaar, 2004), P-technique dynamic factor analysis (Molenaar, 1985), "association models" (zero-order correlations and zero-order cross-lagged autocorrelations), regularized graphical vector autoregressive (VAR) models (Wild et al., 2010; Epskamp, Waldorp, et al., 2018), unified structural equation models (SEM; Fisher, Reeves, Lawyer, Megdalia, & Rubel, 2017), and GIMME models (Beltz et al., 2016). Each of these models rely on similar estimation techniques and similar sets of assumptions but differ in a few critical ways.

The purpose of P-technique factor analyses is to "ascertain the structure of intra-individual variation" (Molenaar, 1985, p. 181). Like factor analysis applied to between-person relationships, the goal of P-technique factor analyses is data reduction – that is, to determine whether the observed multivariate time series can be seen as emerging from a latent factor series of reduced dimensions. The main difference between P-technique factor analysis and P-technique dynamic factor analysis is that the latter accounts for the lagged covariance matrix in order to more accurately estimate the time-independent structure of the unlagged covariance

matrix. However, there are a few critical weaknesses of P-technique approaches that limit their appeal. First, they do not address the interactionist /contextualist critiques of nomothetic assessments as they cannot not account for variability across contexts. Second, these techniques seek to reduce an individual's responses to a discrete number of a factors. Reduction of indicators to a smaller number of latent factors reduces comparability in personality structure as people likely differ both in number and content of idiographic factors (Allport, 1937).

Recent advances idiographic modeling and network science can overcome P-technique critiques. Network approaches have recently garnered considerable attention, with some touting the great advantages these models offer (Borsboom & Cramer, 2013) as well as some of the downfalls (Forbes et al., 2017; Bos et al., 2017; although see Borsboom et al., 2017 for a contrasting opinion), particularly in cross-sectional research that does not utilize time series designs. Networks highlight relationships among indicators, visually and quantitatively representing complex relationships between indicators that reveal both direct and indirect relationships between them. Moreover, idiographic networks are better suited to answering questions of intraindividual personality processes that are not easily testable within factor models (see Beck & Jackson, 2017²). Unfortunately, only a few studies have used network science to examine personality, and of those that have, none have used networks to conduct idiographic assessments of personality, nor looked at networks longitudinally. One cross-sectional examination of the network structure of Conscientiousness (Costantini & Perugini, 2016) found that network models largely replicate traditional factor models (e.g. Jackson et al., 2009 for a non-network approach). Currently it is unclear to what extent networks models can be used with

² This paper was a brief comment demonstrating the utility of using network approaches to idiographic time series data to understand structure, processes, and development. The present paper goes beyond that by offering a fuller discussion of the background an importance of these idiographic time series models, including a number of different kinds of idiographic time series models, and utilizing the full sample in the present study.

time series personality data, to what extent they can be used for idiographic assessment, and whether they can be effectively utilized longitudinally.

Importantly, what makes a network model is not an estimation procedure but the methods that can be applied to data or results structured as matrices.³ In the present paper, we use graphical VAR models, which find a “sparse” solution to directional relationships among indicators using a technique called graphical LASSO on the inverse covariance matrix (i.e. the partial correlation matrix; Friedman et al., 2008; Rothman, Levina, & Zhu, 2010; Wild et al., 2010). But graphical VAR is not unique in generating estimates of these relationships. Indeed, the most important question when considering whether representing and understanding data or models from a network perspective concerns the definitions of the nodes and edges (Beck & Jackson, 2019a, 2020; Piccirillo, Beck, & Rodebaugh, 2019). For example, should the lowest-level measurement unit be items or should the items be composited into higher-order constructs? Perhaps even more important than the definition of the nodes is the definition of the edges, which can represent adjacency (or co-occurrences), correlations, partial correlations, frequencies, individual differences, and more (c.f. Beck & Jackson, 2019a). For the purpose of this paper, we study so-called contemporaneous and lagged relationships. Contemporaneous relationships gauge probabilistic within-person same time point relationships – that is, the tendency for two manifestations of personality to occur at the same time – and can be thought of as “while” relationships. Lagged relationships, in contrast, estimate probabilistic within-person, cross-time point (or cross-lagged) relationships – that is, the tendency for two manifestations of personality to follow the other across measurement occasions – and can be thought of as *if...then* relationships.

³ Throughout this paper, we will sometimes use the term “network model” to refer to VAR models and other time series models whose results can be represented in matrix form. Moreover, we will use the term “edges” to refer to coefficients from the VAR and other time series models.

Other types of models such as association models, GIMME models (Beltz & Gates, 2017; Wright et al., 2018), and unified SEM models (e.g. Fisher et al., 2017) can be applied to multivariate time series in order to estimate similar idiographic relationships among indicators. The simplest, association models, sidesteps the possibility of overcontrolling that occurs when using multivariate models (Forbes et al., 2017). Rather than looking at the relationships among unique variances among all indicators, such models examine all overlapping variance among indicators.

Unified SEM (uSEM) models make use of SEM to estimate similar cross-lagged associations as vector autoregressive models. Unified SEM is a technique used to simultaneously estimate lagged and contemporaneous relationships among time series indicators that bridges the gaps between VAR models and SEM. uSEM uses an automated search procedure to select the paths and, unlike MLM, is truly idiographic (i.e. there is no shrinkage of individual-level estimates; Gates & Molenaar., 2012). The GIMME procedure is a technique for merging truly idiographic estimate estimates with group-level estimates. Like multilevel models, GIMME models estimate both between- and within-person effects simultaneously, where the there is dependence between individual-level and group-level estimates. However, selection criteria for paths using the GIMME procedure differs from MLM-like estimation in the direction of dependence between individual-level and group-level estimates. Rather than simply estimating “average” relationships, the GIMME procedure keeps group-level paths that are significant for at least 75 percent of individuals and prunes paths not significant for at least 75 percent of the sample. As currently implemented, for individual-level models, rather than using a regularization technique to prune paths, GIMME uses uSEM to select the paths although other models can be implemented in the place of uSEM.

Although each of the above-mentioned models are capable idiographic modeling techniques, we believe that models that test both within-time (also known as lag 0 or contemporaneous) effects and cross-lagged (i.e., lag 1 or simply “lagged”) associations among indicators are a key development in the study of idiographic personality. Unlike techniques meant to reduce the dimensionality of the data in order to ascertain the structure of patterns of the level of indicators, network tools allow researchers to investigate intraindividual personality structure and autoregressive models allow researchers to test contextualist (i.e. *if...then* relationships or $p(B|C)$ questions about personality. In the present study, we test various idiographic approaches, but highlight the results from the graphical VAR models for two reasons. First, relative to other lagged or autoregressive models, it was the first developed (c.f. Wild et al., 2010), so we chose to treat it as the test case. Second, we used graphical VAR because our primary interest was estimating models that are $N = 1$ estimates and not in estimating a unified group-level model (as a multilevel VAR model or GIMME model are also meant to do).

The Present Study

Given that idiographic time series models represented as networks have not been utilized in the study of personality, there is a critical need to better understand patterns of structure and development in idiographic networks before tackling questions of process (Beck & Jackson, 2017). The present study had two broad goals. First, we seek to demonstrate the utility of interpreting individual-level, idiographic models. Idiographic techniques are rarely implemented in psychological science, partly due to the lack of appropriate methods. In the current study, we provide a number of ways that idiographic models can be used to both understand the individual person, as well as to support broader claims about personality development at the between-person level.

Second, we seek to investigate the consistency of idiographic personality networks across time. Using a two-year, two-wave ESM study, we seek to test the consistency and reliability of network approaches to time series personality data. Idiographic models will be fit for each participant to provide a more nuanced view of how people change compared to traditional between-person questionnaire approaches. No studies to date have longitudinally examined the consistency or development of individual idiographic models over years. Three main questions are addressed: First, how do we interpret the structure of idiographic lagged and contemporaneous models? Second, how consistent are idiographic assessments of personality over time, on average? Third, how much variability (i.e. individual differences) is there in idiographic personality development?

Method

Participants

Undergraduate students at Washington University in St. Louis completed experience sampling method (ESM) surveys across two waves as part of the longitudinal Personality and Interpersonal Roles Study (PAIRS; Vazire et al. 2015)⁴. For Wave 1, 417 (136 males, 279 females) students with a mean age of 19.44 ($SD = 2.33$) completed ESM surveys. Some participants also completed a Wave 2 ESM assessment. Of these participants, some completed Wave 2 one year after Wave 1 ($N = 207$, 58 males, 147 females, 2 unknown, mean age of 19.20 ($SD = 2.09$)), while some $N = 134$ students with a mean age of 19.0 ($SD = 1.67$) completed Wave 2 roughly 2 years after Wave 1 (29 males, 99 females, 6 unknown). To facilitate interpretation, these later two assessments were collapsed, resulting in a sample of 217 students (56 males; 160 females, 1 unknown) with a mean age of 19.3 ($SD = 2.06$) at wave 2. For each wave, participants were paid \$20 for the laboratory portion of each assessment and entered into a lottery with the

⁴ Data from this study have previously been published elsewhere (c.f. Sun & Vazire, 2019; Sun, Schwartz, Son, & Vazire, 2019; Wiedman et al., 2019; Wilson et al., 2017).

chance to win \$100 for completing ESM surveys (if all ESM surveys were completed, the odds of winning were 1 in 10). Participants' self-reported ethnicities indicated that 56% identified as Caucasian, 23% as Asian, 9% as Black, and 12% as other. 2% of participants did not report their ethnicities. This study was approved (IRB#201206090) by the Institutional Review Board at Washington University in St. Louis.

Materials and Procedure

Before completing the ESM component, participants first completed a two-hour laboratory experiment in which they completed multiple questionnaires as well as several other tasks, which will not be considered in the current study. After completing the laboratory portion, the researchers provided participants with instructions on the ESM component of the study. Participants received four emails per day with links to the ESM survey for two weeks. Including a practice survey, there were thus 59 possible surveys for each participant.

Participants responded to questions about their situation, emotions, and behavior in the last hour. The nine personality items were taken from the BFI-44 (John, Naumann, & Soto, 2008), but were modified to reflect the collection periods of the ESM surveys (e.g. "From 5-6 pm, how engaged were you?"). The full item text for each item, as well as descriptive statistics, are shown in Table 1. As noted in Wilson, Thompson, and Vazire (2016), "The shortened BFI scale was comprised of two items per construct taken from the original BFI-44, making sure that each item (a) made sense at the state level; (b) assessed a different facet of the respective Big Five construct; (c) avoided difficult vocabulary words, and (d) had a comparatively high item-total correlation" (p. 4). Participants responded on a 5-point scale from 1 "Not a lot" to 5 "Very." With the exception of Agreeableness items (2), which were only collected if the participant indicated they were interacting with someone in the previous hour, participants responded to all

items at each measurement point. In addition, items from the Openness to Experience domain were not included.⁵

Table 1 about here

Participants completed a total of 15,563 ESM surveys in Wave 1 and 9010 ESM surveys in Wave 2. Before analyzing the data, several exclusion criteria were applied. ESM surveys were excluded if (1) a survey was completed more than 3 hours after it was sent out, (2) the participant was sleeping during the target measurement point, (3) the participant completed less than 75% of the survey items, and (4) the participant provided the same response for 70% or more of the items. This resulted in a sample of 11,540 surveys (Wave 1) and 6623 surveys (Wave 2). In addition, participants who completed fewer than 10 ESM surveys were excluded, yielding final samples of 349 (Wave 1; 106 males, 241 females; $N = 11,124$) and 156 (Wave 2; 43 males, 113 females; $N = 6591$). In the final samples, the median number of completed surveys was 41 (Wave 1; range 11 to 54) and 33 (Wave 2; range 54 to 148)⁶.

Analysis Plan

⁵ The decision to exclude Agreeableness items when participants did not indicate they were interacting with another person and Openness items throughout the full procedure reflects choices made by the research team who initially collected these data. Agreeableness items were restricted because kind and rude behavior (the two Agreeableness items collected) were thought only to be relevant in the context of social interactions. This created a total of 1969 missing values in wave 1 and 1265 missing values in wave 2. Because the number of missing values differ across people, it is useful to also consider the proportion of missing values for each person at each wave. The average proportion of missing values for each person was .19 ($SD = .13$, range .02 to .70) in wave 1 and .21 ($SD = .16$; range .01 to .92) in wave 2. These missing values were handled by using the within-person average for those time points. To ensure that our results were not biased by this choice, we a subset of the analyses in this paper (1) excluding the Agreeableness items all together and (2) excluding all observations where participants were not interacting with the others. Results concerning consistency and individual differences were nearly identical.

Openness was not included because state level descriptors adapted from the BFI were thought to have rarer base rates (e.g., is inventive) and comprised of values and preferences (values artistic experiences).

⁶ In wave 2, longer time series were intentionally collected from some participants.

Idiographic models. We estimated idiographic models at each wave, which we represented as networks.⁷ For all models, lagged and contemporaneous models were estimated. A lagged model estimates time-series predictions – that is, how well each node predicts each other node at the next time point. To estimate the lagged effects, we use lag 1 factorization ($t \rightarrow t+1$); however, because of the speed of psychological processes, the lag 1 factorization, which for our data represents approximately 4 hours, may be too long to capture psychological dynamics. In such situations, it is useful to also consider contemporaneous effects, or how well nodes predict other nodes at the same time point. Together, contemporaneous and lagged models provide insight into both longer scale temporal patterns as well as immediate patterns. In other words, they allow us to understand how momentary changes within the system (contemporaneous effects) may cause stable changes in the system that endure for several hours (lagged effects).

For the primary idiographic models, we estimate a Gaussian graphical model (GGM) variation of the vector autoregressive model (VAR), which estimates a partial correlation matrix in which correlations represent the correlation between variables after conditioning on all other variables (a graphical VAR model; Wild et al., 2010). The lagged and contemporaneous networks are estimated sequentially, such that the contemporaneous networks are estimated using the residuals of the lagged networks to detrend participants responses (e.g. Flury & Levri, 1999). To prevent overfitting, these models are regularized using a variant of the *least absolute shrinkage and selection operator* (LASSO; Tibshirani, 1996), graphical LASSO (glasso; Friedman et al., 2008). Essentially, regularization uses a soft-order constraint to prevent overfitting. Edges that fall below the constraint are set to 0, which effectively reduces the

⁷ We also estimated a between-person networks as an average, or reference, structure to which to compare the idiographic models. These analyses are explained in detail in the online materials on the OSF and GitHub.

dimensionality of the network. *glasso* includes a tuning parameter that can be set to control the sparsity of the network (the elements that are set to 0). Different values of the parameter can be chosen to optimize prediction accuracy to minimize an information criterion, such as the Bayesian information criterion (BIC) or the extended BIC (eBIC; Chen & Chen, 2008). Because our participants responded, on average, to fewer than 50 valid ESM surveys, we set the eBIC hyperparameter (gamma) to 0 because simulation studies suggest that specificity, sensitivity, and the correlation between true and estimated edges for short time series perform best under these circumstances (see Epskamp, 2016b Figures 2-4). Notably, when the hyperparameter gamma is set to 0, the information criterion is simply BIC. Additionally, we allowed the *glasso* lambda parameters to vary between .025 and .25 because we observed that lambda parameters above .25 resulted in almost completely sparse networks, and lambda values of 0 would be fully unregularized networks.⁸ Each graphicalVAR model was implemented using the *graphicalVAR* package in R (Epskamp, 2015).

Centrality. For each model, we also estimate several quantitative indices of network structure. Centrality refers to the relative importance of a focal node to the structure and dynamics of a network (Freeman, 1979). In other words, it provides information about a node's role in the context of other nodes. Although the role of centrality in aiding the interpretation of psychological relationships represented as networks remains uncertain (Bringmann, 2016; Bringmann et al., 2019; Epskamp, 2016a), we believe that centrality indices as a concept remain useful tools for examining node (or indicator)-level properties when examining multivariate time series data of psychological indicators. Indeed, nodes differ in their importance in the network. Compared to other nodes, some nodes are connected to more nodes and/or, in the case of

⁸ However, for the sake of transparency, parallel analyses using a wider range of lambda values (.025 to .5), a fixed lambda value scaled by the length of the time series ($n * .01$), and a fixed lambda value set to 0 were also conducted. The full results of these analyses are included in the online materials on the OSF and GitHub.

weighted networks, have stronger connections to other nodes. Strength centrality is defined as the absolute value of the sum of the weights of the edges that connect a node of interest to other nodes (Barrat, Barthélemy, Pastor-Satorras, & Vespignani, 2004).⁹ In directed networks, strength centrality is broken down into in-strength and out-strength centrality. In-strength centrality is the sum of the absolute value of weights that converge on a node of interest, while out-strength centrality is the sum of the absolute value of weights that diverge from a target node. In other words, a node high in either in- or out-strength has strong connections within the network, but a node high in out-strength strongly predicts other nodes, while a node high in in-strength is strongly predicted by other nodes. All centrality measures were examined using the *qgraph* package in R (Epskamp, Cramer, Waldorp, Schmittman, & Borsboom, 2012).

Other models. To address the possibility that model choice influences our outcomes, we also conducted a series of analyses using alternative idiographic models and alternative hyperparameters and tuning parameters within the graphical VAR procedure. Specifically, we estimated GIMME models using the *gimme* package in R (Lane, Gates, Molenaar, Hallquist, & Pike, 2016), P-technique factor analyses and dynamic factor analyses (and parallel analysis) using the *psych* package in R (Revelle, 2017), association networks using base R, and additional variants of the graphical VAR procedure using the *graphicalVAR* package in R (Epskamp, 2015). The full results of all of these models can be found on the Open Science Framework (<https://osf.io/fyxza/>), GitHub (<https://github.com/emoriebeck/Idiographic-Network-Consistency>), and a Web Application (https://emoriebeck.shinyapps.io/pairs_graphicalvar/).

⁹ Notably, there are several other measures of centrality often used in psychological networks that we do not include. Specifically, we do not include betweenness or closeness centrality as their interpretation in lagged VAR networks is an open debate (Epskamp, 2016a). For example, a direct connection represents a lag 1 relationship. However, two nodes who exhibit only an indirect relationship with one another (the definition of betweenness) represent a lag 2 relationship within a lagged VAR network, even though the lag 1 VAR model only tests a lag 1 relationships. Because closeness and betweenness only consider the shortest path between nodes, they do not account for the time metric between nodes, making their meaning suspect.

Results

How Can We Interpret Idiographic Personality Models as Networks? An Example

Idiographic models (one lagged, lag 1 autoregressive model and one contemporaneous, residual model for each wave) were fitted for each individual. Across all subjects, a total of $N = 976$ networks were created for each model type (e.g. graphical VAR). To elucidate what information these idiographic models can offer, two example subjects are discussed. Figures 1 and 2 present the results of the idiographic graphical VAR models for Subjects 1 and 2 represented as networks.¹⁰ The full results for each of the models, as well as those for all other participants are available in an online web application (https://emoriebeck.shinyapps.io/pairs_graphicalvar/). Notably, the structures of the idiographic networks differed markedly from one another, both locally at the level of edges and globally at the level of network. Below we discuss the important components of these models, thereby demonstrating the different insights that can be gleaned from an idiographic analysis.

Edge weights: What is the structure of idiographic personality networks? In the graphical VAR models, edge weights refer to the relationships between indicators and can be interpreted like partial correlations. Collectively, when represented in matrix form, they define the structure of a single person's network. Consider Subject 1 and 2's idiographic lagged and contemporaneous personality networks for Waves 1 and 2 in Figures 1 and 2. Contemporaneous networks are undirected and do not have feedback loops – that is, lagged precedence is unclear as these associations reflect behaviors occurring at the same time (see Figure 1). Looking at Subject 1's contemporaneous network in Wave 1, the lazy (C) node appears in the center of the network and exhibits several strong positive (e.g. relaxation (N)) and negative connections (e.g. outgoing (E)) to other nodes. Intriguingly, the lazy (C) node has a negative connection with

¹⁰ The example Subjects' original identification numbers were 22652 and 91339, but we refer to them as Subjects 1 and 2 throughout the results for convenience.

feeling reliable (C) and a positive connection with feeling quiet. Subject 2's laziness is also negatively tied to feeling reliable (C) but conditionally independent of feeling quiet (E). Thus, Subject 1's seems to not to feel lazy (C) when quiet, while Subject 2's laziness (C) is untied to whether they are quiet (E) or not, which may have implications for their longitudinal behavioral patterns (e.g. Subject 1 may talk to others more to feel less lazy, while this may not be effective for Subject 2).

We can also consider broader patterns across waves. The strongest edge in Subject 1's contemporaneous networks in both waves was between the two Conscientiousness items (reliable (C) – lazy (C): $r_{W1} = -.59$; $r_{W2} = -.57$). Indeed, many of the strongest relationships within Subject 1's contemporaneous networks were within Big 5 traits (e.g. outgoing (E) – quiet (E); also see additional example Subjects 31974 and 84814 in the online web app). However, the strongest relationships in Subject 2's networks tended to be across, as well as within, domains (also see additional example Subjects 39540 and 84768 in the online web app). Overall, both subjects' associations among nodes were relatively consistent across waves. For example, Subject 1 reported feeling less quiet when they were more outgoing (E; and vice versa; $r_{W1} = -.32$, $r_{W2} = -.52$). However, there were differences across waves, indicating some inconsistency in personality structure.

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Figure 1 about here

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Lagged networks assess how behaviors are related across time (within a wave). In the context of this study, this is four hours later. Each node in a lagged network also includes a feedback loop, which can be interpreted as a partial autocorrelation, deemed inertia in the affect literature when positive (Ong & Ram, 2017) or negative reinforcement patterns when negative (Hamaker, Grasman, & Kamphuis, 2016). As seen in Figure 2, Subject 1's lagged network in the

first wave, the rude (A) node has the most and strongest connections to other nodes, which, in turn, have almost no connections to other nodes. Notably, these are in a single direction – each of the other eight nodes predict reports of rudeness at the next time point. Stated simply, how rude (A) Subject 1 is at a given time is a carry-over effect that largely depends on previous behaviors. Examining the edges in more detail, we see that Subject 1 is more rude after previous reports of being outgoing (E), depressed (N), and relaxed (N) and less rude after reports of being more quiet (E), lazy (C), reliable (C), kind (A), and worried (N).

Interestingly, the feedback loops in Subject 1's lagged networks were notably weak ($\text{rangew}_1 = 0$ to $.07$; $\text{rangew}_2 = 0$ to $.11$), while those in Subject 2's networks were stronger ($\text{rangew}_1 = -.32$ to $.18$; $\text{rangew}_2 = -.02$ to $.25$). These findings indicate that Subject 1's previous behavior did not strongly relate to the same behavior over time, whereas Subject 2's larger auto-correlations indicated inertia in behavior across time. Likely, Subject 2 has relatively greater difficulty modifying behavior across time and context.

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Figure 2 about here

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Centrality: Which indicators are most influential in idiographic personality networks? Thus far, we have considered nodes that appear to be influential by visual examination of the network graphs. We can also quantify the relative importance of nodes in the network using centrality metrics. We examined the local network structure using strength centrality for lagged and contemporaneous networks at each wave. Because the lagged network is directed, we calculated both in-strength and out-strength for each node. For comparison across waves, we z-transformed all centrality results for display in Figure 3 but present the in-text results as raw; the full raw results are available in the online materials on the OSF and GitHub.

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Figure 3 about here

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 Centrality indexes the relative importance of different nodes in the network – that is, nodes’ abilities to directly impact other nodes in the network. At the idiographic level, this represents personality states that are critical to a single person in that they predict many other personality states. Importantly, centrality may show patterns of similarity not evident at the edge level. For example, for Subjects 1 and 2’s wave 1 contemporaneous networks, outgoing (E; $S1 = .75$, $S2 = .90$) was relatively central, but for each subject, the node was connected to different nodes with different strengths. Thus, being outgoing may be an important behavior for both subjects, but in different ways.

Is Idiographic Personality Consistent Across Time?

In the previous section, we used two subjects to demonstrate the insights one could garner with idiographic models represented as networks. Such specific insights – which are time-consuming if one wants to look at a large number of subjects or items – is one reason that idiographic assessment is rare. It is difficult to glean broad population-level insights from models that are specific to an individual. This poses a problem of whether to focus on the trees (idiographic) or the forest (between-person). To shift from a narrow focus to a broader one, we below attempt to draw broader claims from these $N = 1$ models, ultimately addressing whether personality assessed at an idiographic level demonstrates longitudinal consistency.

We assessed the consistency of idiographic personality networks over a two-year period using rank-order and ipsative correlations of both network edge weights and centrality indices.¹¹ For comparison purposes, we also created a composite of ESM assessments averaged over the

¹¹ The reference frame for measures of rank order and profile consistency are different. Rank-order consistency is variable centered. It indexes the consistency of between-person individual differences – are people who are higher than most in a measure at one time point also higher than most in another? Profile consistency, in contrast, is person-centered. It indexes the consistency of within-person individual differences – does one individual tend to be higher or lower than others across the same indicators at different time points?

assessment period to examine more traditional nomothetic measures of rank-order and ipsative consistency¹².

Edge weight consistency. First, we examined rank-order and ipsative consistency of the 36 edge weights of the idiographic contemporaneous networks. For rank-order consistency, a variable-centered measure of consistency, we assigned ranks for each edge for each participant at each wave based on their edge weights. Next, we used the ranks to calculate rank-order correlations, resulting in 36 unique rank-order correlations (1 per edge). Rank-order consistency highlights the relative consistency of edges across participants (interindividual differences in consistency). As shown in the left panel of Figure 4, rank-order correlations of contemporaneous edges were weak to moderate ($M = .10$, $SD = .10$, range $-.10$ to $.34$), ranging from $-.06$ (reliable (C) – depressed (N)) to $.35$ (outgoing (E) – quiet (E)). Notably, within-domain edges ($M = .24$, $SD = .12$, range $.03$ to $.34$) were more consistent than between-domain edges ($M = .07$, $SD = .08$, range $-.10$ to $.32$). Extraversion, Agreeableness, and Conscientiousness items exhibited the strongest rank-order consistency.

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Figure 4 about here

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Next, we assessed the ipsative consistency of individuals' contemporaneous edge weight profiles across the waves. Ipsative consistency highlights the relative consistency of all edges within participants (intraindividual differences in consistency). When one individual's change in edge weights tends to be in the same direction and at the same magnitude, ipsative consistency is

¹² For comparison purposes, we also created a composite of ESM assessments. We first calculated individuals' mean ratings on each of the personality variable for each wave. We also calculated composite scores for each Big 5 traits at each measurement point. Then, for each wave and item / composite combination, we assigned ranks to participants based on their ESM composites. We used the ranks to calculate rank-order correlations using Spearman correlations, resulting in 14 rank order correlations (1 for each of the 9 items and 4 composites). Overall, consistency of both Big 5 composites ($M = .97$) and items ($M = .91$) was very strong over two years. There were also interindividual differences in intraindividual consistency of both composites ($SD = .66$) and items ($SD = .47$). We use these to as a benchmark to which to compare rank order and ipsative consistency of idiographic networks.

high. When direction and/or magnitude of change are different, ipsative consistency is low.

Using a Fisher transformation, we found that the average profile correlation for the idiographic contemporaneous networks was a modest to high $r = .62$, indicating relative idiographic intraindividual consistency across time.

In comparison with traditional nomothetic composites created from ESM items, the idiographic measures showed less consistency. Rank order consistency was fairly high across the two years for both nomothetic items (range .46 to .74) and trait composites (range .68 to .79), whereas the nomothetic ipsative consistency was ($M = .97$) for composites and ($M = .91$) for items.

We next completed a similar procedure for each of the 81 edge weights in the idiographic temporal, lagged networks. As shown in the right panel of Figure 4, rank-order consistency of lagged edge weights was weak on average ($M = .01$, $SD = .09$, range -.23 to .31). However, several edges showed non-trivial patterns of rank-order consistency. For example, an $r = -.24$ for reliable (C) \rightarrow relaxed (N) and an $r = .25$ for kind (A) \rightarrow relaxed (N) indicated that precursors to feeling relaxed are modestly consistent across a two-year period. For ipsative consistency, we again calculated profile correlations for each participant across the two years. The average profile correlation of idiographic lagged networks was low ($M = .03$).

Centrality consistency. Next, we assessed contemporaneous centrality indices' rank-order and ipsative consistency using the same methods as with edge weights. Strength centrality showed relatively modest to low rank-order stability across the waves ($M = .19$, $SD = .07$). As with edge weights, though, rank-order consistency varied across indicators, ranging from .12 to .32. The worried node (N) exhibited the weakest rank-order consistency ($r = .12$), while the quiet node (E) exhibited the strongest ($r = .32$). Finally, ipsative consistency of strength centrality was

strong ($M = .61$), indicating that the most important and least important nodes for each person are consistent across two years.

We next assessed the rank-order and ipsative consistency of the centrality indices for the idiographic lagged networks. In contrast to lagged network edge weight rank-order consistency, both in-strength ($M = .18$, $SD = .04$) and out-strength ($M = .19$, $SD = .06$) showed modest to low consistency across two years. Rank-order consistency of lagged in-strength and out-strength varied across indicators, with in-strength ranging from .12 (depressed (N)) to .23 (lazy (C)), and out-strength ranging from .12 (relaxed (N)) to .26 (outgoing (E)). Finally, we assessed the ipsative consistency of in- and out-strength over 2 years. Profiles of in-strength ($M = .37$) and out-strength ($M = .22$) showed small to modest consistency, indicating that the nodes within lagged relationships among variables are relatively stable across two years.

Disentangling consistency from reliability. In considering consistency, it is important to separate “true” consistency from measurement error. Because the reliability of idiographic network models is unexplored, measurement error may contribute to consistency estimates lower than the ESM reliability composites. To gauge the reliability of our idiographic networks, we examined person-level reliability within waves to disentangle longitudinal consistency from the reliability of the network models. To do so, we both (1) split each participant’s data in half at each wave and (2) split each participant’s data into two sets containing either odd- or even-numbered observations. For each split (half and odd v. even), we constructed idiographic lagged and contemporaneous networks for each and calculated the profile correlation between the two halves. This resulted in two lagged and two contemporaneous networks for each participant at each wave for each type of split, for a total of 8 per participant. Split-half ($M_{W1} = .001$, $SD_{W1} = .14$; $M_{W2} = .03$, $SD_{W2} = .17$; see Figure 5) and odd-even split ($M_{W1} = .01$, $SD_{W1} = .15$; $M_{W2} = -.002$, $SD_{W2} = .17$) network profiles of lagged networks were much less stable than split-half

($M_{W1} = .40$, $SD_{W1} = .29$; $M_{W2} = .49$, $SD_{W2} = .33$) and odd-even split ($M_{W1} = .43$, $SD_{W1} = .29$; $M_{W2} = .50$, $SD_{W2} = .31$; see Figure 5) contemporaneous networks.

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Figure 5 about here

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However, there was considerable variation in reliability at the individual level, indicating reliability can be considered an individual difference. In wave 1, contemporaneous split-half reliability ranged from -.32 to .92 (range W2 -.34 to .96) and odd-even reliability ranged from -.19 to .99 (range W2 -.19 to .98). Subject 1 showed both strong contemporaneous consistency as well as split-half ($r_{W1} = .74$; $r_{W2} = .79$) and odd-even ($r_{W1} = .72$; $r_{W2} = .67$) reliability at both waves. Despite showing strong cross-wave contemporaneous consistency, Subject 2, in contrast, showed poor contemporaneous split-half ($r_{W1} = -.12$; $r_{W2} = -.34$) and odd-even ($r_{W1} = .15$; $r_{W2} = -.03$) reliability in both waves. Reliability and consistency were associated, which likely indicates that those with poor consistency may have more variable state-level behaviors. The poor consistency of the lagged idiographic networks suggests that their structure and stability within and across years should be interpreted cautiously.

Are there Individual Differences in Idiographic Network Consistency?

The above section dealt with the average rank and ipsative consistency across contemporaneous and idiographic models. What these estimates gloss over, however, are individual differences in consistency.¹³

Individual differences in network edge consistency. While ipsative consistency of contemporaneous edge weights was quite strong on average, there was considerable variability in consistency ($SD = .42$). The left panel of Figure 6 provides a histogram of individuals' ipsative

¹³ An alternative way to index individual differences in network structure is to examine the standard deviation of edge weights for both contemporaneous and lagged idiographic networks (see the online materials on the OSF and GitHub).

consistency, showing that across the whole sample, consistency ranged from $-.19$ (Subject 9627) to $.93$ (Subject 9006). Both Subject 1 ($r_{S1} = .77$) and Subject 2 ($r_{S2} = .65$) exhibited strong consistency in contemporaneous network structure over two years. In other words, for both subjects, within-time point associations between-personality states were quite consistent across time.

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Figure 6 about here

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While the ipsative lagged networks' consistency was not strong on average, the distribution of profile correlations suggest that some subjects were relatively consistent (right panel of Figure 6). Correlations ranged from $-.44$ (Subject 64696) to $.55$ (Subject 97049).¹⁴ While our example Subject 1 ($r_{S1} = .55$) exhibited strong lagged consistency, Subject 2 had low lagged network consistency over 2 years ($r_{S2} = .12$).

Individual differences in centrality consistency. Similar to edge weights, centrality measures showed variability in ipsative consistency ($SD = .48$; see Figure 7), ranging from $r = -.58$ (Subject 56105) to almost perfect consistency of $r = .97$ (Subject 28861). As seen in Figure 3, Subject 1's centrality profile ($r_{S1} = .72$) is more consistent than Subject 2's ($r_{S2} = .40$). Ipsative centrality consistency was consistent with ipsative edge weight consistency, with a correlation between ipsative edge weight consistency and centrality consistency of $.75$. That is, subjects who are consistent in their edge weights also tend to have consistent centrality metrics.

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Figure 7 about here

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¹⁴ We also calculated each profile correlation by first centering all edge weights within persons and waves. Doing so resulted in essentially no change in stability estimates, so we present profile correlations of uncentered edge weights. The stability of centered edge weights are available in the online materials on the OSF and GitHub.

The ipsative consistency of lagged edge weights was much lower than that of in-strength and out-strength centrality estimates. However, both in-strength ($SD = .44$) and out-strength ($SD = .36$) showed considerable variability in consistency. In-strength consistency ranged from $-.47$ (Subject 56105) to $.97$ (Subject 10623), and out-strength consistency ranged from $-.71$ (Subject 11260) to $.96$ (Subject 38264). These findings indicate that averaging over the sample misses important consistency, further highlighting the need to look at each person individually to understand personality consistency. Interestingly, there is almost no correlation between ipsative edge weight and either in-strength ($r = .02$) or out-strength ($r = .01$) consistency.

How Do Graphical VAR Models Compare To Other Models?

Graphical VAR models are one method for estimating the idiographic structure of time series data, but there are a number of alternative idiographic models that can be specified, some of which can also be represented as networks. In large part, these models can be broken down into two classes – (1) models that attempt to *reduce* the data to a smaller number of dimensions (P-technique factor analysis), where the goal is to understand patterns and structure in the level of indicators and (2) models that attempt to capture the complexity of the indicators (graphical VAR, GIMME, association), where the goal is to understand unique patterns of associations between indicators and their relationship to time. In other words, these models differ on the question of dimensionality of the data and the treatment of time in the model. Among the models meant to capture complexity, which can be represented as networks, we see these models as largely interchangeable, as they are meant to capture patterns of contemporaneous and lagged relationships in multivariate time series. In evaluating the consistency of idiographic personality, we also computed analyses for these alternative models as a comparison to the VAR models. In addition, we provide alternative graphical VAR models that varied certain parameters of the

model to assess whether estimates are robust. The online materials on the OSF and GitHub include the full results of each of these models.

Table 2 presents descriptive statistics of rank-order consistency of lagged and contemporaneous (1) regularized partial correlation graphical VAR models that also tested stronger penalization (maximum regularization hyperparameter lambda set to .50), (2) regularized partial correlation graphical VAR models where the maximum penalization was scaled by sample size (maximum regularization hyperparameter lambda set to $.01 * n$), (3) unregularized partial correlation graphical VAR models, (4) unregularized zero-order correlation (association) matrices, (5) GIMME models (Beltz & Gates, 2017; Beltz et al., 2016), (6) empirical Bayes estimates from a series univariate multilevel vector autoregressive models (Bringmann et al., 2016), and (7) P-factor analyses and dynamic P-factor analyses. The pattern of results for each model largely replicates the pattern of results of the graphical VAR models presented previously. Contemporaneous rank-order consistency is, on average, higher than lagged rank-order consistency, with the exception that dynamic (lagged) factor analyses had slightly higher rank-order consistency ($M = .08$, $SD = .05$, range .01 to .16) than contemporaneous factor analyses ($M = .05$, $SD = .12$, range -.14 to .17).

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Table 2 about here

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Figure 8 presents the ipsative consistency of lagged and contemporaneous of the same models. As is clear in the figure, the distributions of ipsative consistency were quite similar across methods, with the exception of the empirical Bayes estimates of the multilevel VAR models, which tend to show higher consistency. The higher consistency of the empirical Bayes estimates likely occurs because the estimates are “shrunk” and reliability corrected by the multilevel procedure, resulting in estimates that reduce variability and limit extreme estimates of

edge weights. When this occurs, estimates of ipsative consistency are higher because deviations across waves become smaller on average. Similarly, the eigenvalues of P-technique factor analytic models show strong two-year consistency. In large part, this simply indicates that the variability in each of the indicators was similar across two years, which is not surprising given evidence that within-person variability is a valid and reliable individual difference variable (Fleeson, 2001). Across other models, the distribution of individual differences was similar (see the online (OSF and GitHub) and the web app for full results).

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Figure 8 about here

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Discussion

In an effort to get closer to the person, the current study examined personality development from an idiographic perspective. This study was the first to examine contemporaneous and lagged VAR models represented as networks longitudinally to investigate idiographic consistency in personality. Two broad goals were addressed. First, we hoped to demonstrate the utility of interpreting idiographic, individual-level models in an effort to encourage future research at a more fine-grained level, where understanding development does not need reference to a broader group but instead can be interpreted through one's own configuration of personality manifestations. Second, we hoped to examine the general consistency of idiographic personality assessments to see if the pattern of consistency (and individual differences in consistency) paints the picture of a consistent or mutable personality system. The present study improved upon previous studies of idiographic personality assessment and modeling in several ways. First, we improved upon structural approaches to idiographic personality by utilizing repeated measures ESM data with idiographic autoregressive models that allow for complexity and temporal patterns of rather than reducing them as in P-technique factor

analysis. Second, we directly estimated time-dependent patterns in the data rather than simply examining bivariate within-person associations. Third, we also improved upon contextualist approaches to idiographic assessment by probabilistically modeling *if... then* and *while* relationships among manifestations of state personality rather than looking at average levels of personality in specific contexts. This novel approach allowed us to investigate the consistency of patterns of behavior across time, both concurrent patterns, as well as directional patterns separated by time. Overall, we demonstrated the richness of insight modern idiographic modeling techniques coupled with network approaches offer and found relative consistency in personality across a two-year period, particularly for contemporaneous models. While this consistency was lower than traditional personality assessments, these estimates masked large heterogeneity in idiographic personality consistency. Below we elaborate on these points to discuss how idiographic models may be utilized to better understand personality development.

Idiographic Assessments of Personality

Our results suggest considerable heterogeneity in idiographic personality structure. We observed individual differences for both within-trait and across-trait relationships, as well as for centrality indices. Our results provide convergent evidence for a limited body of research investigating how people manifest the same personality traits differently and how individual-level personality structure does not necessarily match the Big Five structure (e.g. Cervone, 2005; Cervone, Orom, Artistic, Shadel, & Kassel, 2007; Fournier, Moskowitz, & Zuroff, 2008; Kuppens, van Mechelen, Smits, De Boeck, & Ceulemans, 2007; Mischel & Shoda, 1995; Shoda, Mischel, & Wright, 1993; Wright & Mischel, 1987; Wright & Zakriski, 2001, 2003; Wright et al., 1999). Such patterns call into question the exclusive use of broad trait summaries and highlight the importance of an increased emphasis on idiographic, contextualized assessment. Our results are consistent with the idea that nomothetic models predict “some people some of the

time” (Bem & Allen, 1974) whereas idiographic assessments capture differences among people that are missed in between-person models.

Idiographic assessments also allow the identification and direct examination of individuals who may be of particular interest. For example, the outgoing (E) – quiet (E) edge would typically evidence a negative relationship between feeling outgoing and quiet. Yet there was a substantial minority (~10%; see Subject 35045) of individuals who felt outgoing when they were quiet. Likewise, a fair amount of people tend to feel more depressed when they are quiet (a positive quiet (E) – depressed (N) edge; ~ 25%; see Subject 13266) but a non-trivial amount are less depressed when they were quiet (~7%; see Subject 49055). Such divergent patterns are captured at the idiographic level but are all but missed with between-person approaches, highlighting the importance of continued idiographic research.

One way in which idiographic models capture missed information in between-person models is through insight into relationships among behavioral manifestations of personality. These behavioral patterns, at the surface, seem to address the idea of *if...then* contingencies in personality (Wright & Mischel, 1987; Mischel & Shoda, 1995), which conceptualize personality as sets of linked behaviors that tend to follow other behaviors. Our findings indicate different contingent patterns in the idiographic contemporaneous and lagged models. Strong edges in the contemporaneous models were rarely strong edges in the lagged models, which may mean that some personality manifestations immediately impact other manifestations, while others’ impacts unfold more slowly over time. In other words, *while* (i.e. *contemporaneous*) relationships differ from *if...then* (*lagged*) contingencies. Examining only one type of relationship fails to capture a full picture of personality. The extant literature on *if...then* contingencies largely relies on self-reported contingencies (e.g. “If I am anxious, then I lash out”; Endler & Hunt, 1969; Vansteelandt & Van Mechelen, 1998; Kuppens et al., 2007), which leaves interpretation of the

time scale of the contingency to the respondent. Yet few have considered the importance of the time scale on which personality manifestations unfold (for an exception see Ram, Brinberg, Pincus, & Conroy, 2017), and none, to our knowledge, have this addressed empirically, leaving a critical hole in our understanding of the manifestation of personality across and within both time and people.

Idiographic Consistency

Contemporaneous idiographic models showed moderate ipsative and rank-order consistency of personality across two years. At the level of the individual, behavioral patterns were consistent and, if there was change, people tended to change in similar directions and to similar degrees. Across all the examined models, it is striking how similar the patterns of consistency were. With the exception of P-technique factor analytic models and the empirical Bayes estimates from multilevel VAR models, association, graphical VAR (with varying penalization hyperparameters), and GIMME models showed almost identical consistency estimates over two years. These findings suggest that consistency findings are not due to analytic choices, as all newer idiographic approaches suggest similar patterns of consistency.

In terms of specific contemporaneous edges across the tested models, some were more stable than others. For example, outgoing (E)-quiet (E) showed modestly high rank-order consistency, while rude (A)-depressed (N) showed none. Notably, the top three edges exhibiting the strongest rank-order consistency were between nodes within the same trait. The moderate rank-order consistency of contemporaneous network edges is nearly as strong as broad dispositional inventories, which demonstrate moderate to high rank-order correlations between .4 and .6 (Roberts et al., 2008). Longitudinal consistency in network edges reflect consistency in state-level associations, in contrast to longitudinal consistency in trait-level, retrospective reports. That idiographic contemporaneous networks of state-level personality manifestations

over two years show comparable test-retest reliabilities to those of nomothetic measures over similar time frames highlights the consistency of many forms of personality.

On average, the lagged idiographic models showed almost no ipsative or rank-order consistency over two years and this pattern largely held across models, with the exception of P-technique factor analytic models and empirical Bayes estimates, which we discussed earlier. There are several possible explanations for the large number of people exhibiting two-year instability in these models. The first is situational – the instability of contingent behaviors reflects changes in the individuals' situations – and reflects methodological challenges (and opportunities) with ESM. Although frequencies of college students' behaviors are relatively stable (Finnegan & Vazire, 2017), their lagged sequence is relatively unstable (Rauthmann, Jones, & Sherman, 2016). In other words, the college students in our sample may, on average, have spent similar *amounts* of time in class or socializing, but the *sequencing* of those behaviors may have strongly differed across the two years of the study. Given that college students' schedules are highly dependent on the constraints of courses and activities, such a possibility seems possible, but future ESM studies should gather information on students' situations and perceptions of situation change (Rauthmann & Sherman, 2016).

Second, the instability of *if...then* contingencies appear to themselves be individual difference variables. That is, some individuals do have contingent behavioral patterns, while others do not to the same degree (Kuppens et al., 2007). Given strong similarity in two-year ipsative and rank-order consistency across examined idiographic contemporaneous and lagged models (as well within those models with different levels of penalization), it appears this lack of consistency is not artifactual but a true property of these data. Indeed, rather than spelling doom for idiographic assessment or the role of *if...then* contingent patterns in personality, the absence of consistent lagged associations may provide critical information. For example, if an individual

was frequently plagued with anxiety that seemed to have to no source, it might disrupt important behavioral patterns, such as self-care practices. Establishing contingent patterns between anxiety and other behaviors may provide a way to reduce anxiety. If anxiety becomes a cue to seek social support, a bidirectional tie between the two may be formed such that high anxiety predicts higher social support, which in turn predicts lower anxiety (Hogan, Linden, & Najarian, 2002). Thus, short- and long-term inconsistency of *if...then* contingencies offers new hypotheses about behavioral patterns that are not captured by traditional assessments.

A third possibility for weak average lagged consistency is that *if...then* contingent measurements were reliably assessed but not functionally defined. As discussed prior, personality manifestations should be considered in the context of the probability of a behavior, $p(B)$, the probability of a behavior in a specific context, $p(B|C)$, and the probability of the evoking context, $p(C)$ (Wright & Mischel, 1987; Wright et al., 1999; Wright & Zakriski, 2003), with $p(B)$ assessed using nomothetic assessments like ESM composites. We addressed $p(B)$ in this paper using contemporaneous models and the conditional probability $p(B|C)$ using lagged models. However, we did not explicitly measure $p(C)$ (e.g. studying or interacting with others), which could potentially explain the instability of lagged assessments over two years. If $p(C)$ is small in one year but not the other, measured $p(B|C)$ will likely change, while there is no reason to assume the actual contingency, which is supposed to represent stable, dispositional patterns, itself changed. We might simply have failed to capture the true $p(B|C)$ when contexts were infrequently encountered. Idiographic assessment, however, is uniquely suited to capture the interplay between $p(B)$, $p(C)$, and $p(B|C)$. Future studies should measure the frequency of encountering evoking contexts, so as to isolate which *if...then* contingencies likely play a more functional role in individuals' daily lives.

Across both lagged and contemporaneous models, the rank-order consistency of centrality indices was stronger than the rank-order consistency of edges. Centrality estimates aggregate across all of a node's connections in the network, assuming that these connections provide insight into how influential a node in the network is. Thus, it could be considered a broader measure of network properties. Because centrality indices aggregate across connections, one possible explanation of strong centrality rank-order consistency is that centrality estimates come close to capturing what has been called "emergence" in both the personality (Baumert et al., 2017) and network (e.g. Barabási & Albert, 1999) literatures. Emergence means that different combinations of microscopic processes can give rise to the same macroscopic properties (Baumert et al., 2017). Another possibility is that strength centrality captures much of the common variance captured in factor loadings in factor analysis (Hallquist & Hillary, 2018). Indeed, the estimates of rank-order consistency was similar for centrality consistency and P-factor consistency. However, a third important possibility is that centrality indices common in work on social networks have little meaning in the interpretation of models of psychological data represented as networks (Bringmann, 2016; Bringmann et al., 2019; Epskamp 2016a). Until psychological scientists have a better understanding of how processes of psychological systems operate, no conclusions can be drawn about whether centrality captures desired properties, like emergence, or undesired, uninterpretable properties of these models.

On the whole, observations of consistency and change in idiographic models highlight how representing time series models as networks is well-suited to examine processes driving personality. Recent work has suggested that antecedents of trait development occur below the trait level at a facet or item level (Mõttus et al., 2015; Jackson et al., 2009; Soto & John, 2012). For example, the passage into middle age from young adulthood is characterized by changes to the Conscientiousness facets of self-reported industriousness, impulse control, and reliability but

not orderliness (Jackson et al., 2009). Along these same lines, changes in broad trait levels are thought to result from prolonged changes in state-level manifestations of the trait (Magidson, Roberts, Collado-Rodriguez, Lejuez, 2014; Roberts & Jackson, 2008). And indeed, personality trait change follows psychotherapy (Roberts et al., 2017) and state level changes in the Big 5 do reflect trait-level changes over the same period (Beck & Jackson, 2019b). However, these state-level manifestations are typically neither examined simultaneously nor incorporated into developmental models. In contrast, idiographic time series models are built using state-level manifestations assessed multiple times of day. Together, these models can both assess lower-order facets as well as state-level manifestations to see whether or not these methods show different patterns of change compared to traditional questionnaires (c.f. Nofle & Fleenor, 2010).

Individual Differences in Consistency

There were individual differences in contemporaneous and lagged consistency over two years – that is, individuals in this sample charted unique developmental courses. Some contemporaneous and lagged behaviors were quite consistent, while others were not. Such a finding aligns with previous research indicating that interindividual differences in intraindividual profile stability form a behavioral signature of sorts that reflects personality coherence (Fournier et al., 2008; Mischel & Shoda, 1995; Shoda, Mischel, & Wright, 1994). In other words, interindividual differences in profile stability are important and welcome, and looking at consistency on average obscures the great consistency that some individuals exhibit. Thus, even though we observed weaker consistency of network profiles compared to nomothetic profiles, the average lagged and contemporaneous consistency across all individuals is far below the upper bound we might expect for any individual.

Unlike the contemporaneous networks, which showed considerable consistency and split-half reliability, the split-half reliability of lagged networks was relatively weak for many

individuals, with almost no relationship on average. However, despite this, there were a number of individuals whose *if...then* (lagged) network patterns showed considerable split-half ($\max_{w1} = .53$, Subject 28861; $\max_{w2} = .58$, Subject 76821) and every-other ($\max_{w1} = .55$, Subject 73719; $\max_{w2} = .61$, Subject 76821) reliability as well individuals whose *while* (contemporaneous) network patterns showed almost no split-half ($\min_{w1} = .001$, Subject 20054; $\min_{w2} = -.02$, Subject 41038) or odd-even ($\min_{w1} = .002$, Subject 90299; $\min_{w2} = -.001$, Subject 59665) reliability.

On the whole, individual differences in stability and reliability of networks highlights the need to investigate psychometric properties of ESM assessments to improve idiographic assessment (c.f. Piccirillo, Beck, & Rodebaugh, 2019). In addition to psychometric concerns, individual differences may reflect that people's manifestations of personality occur at different time courses and due to different contextual triggers. Further, consistency could represent more internal characteristics, such as mental health. Individuals with depression, for example, tend to exhibit a global, stable, and internal attribution style compared to non-depressed individuals (Seligman, Abramson, Semmel, & von Baeyer, 1979), and this attribution changes following recovery from depression (Abramson, Metalsky, & Alloy, 1989). In this sample, individuals with consistent *while* behaviors were somewhat more Agreeable, Extraverted, Conscientious, and compassionate (see the Supplementary Analyses section of the materials on OSF and GitHub), while individuals with consistent *if...then* contingent behaviors were more dominant (a facet of Extraversion not captured in the ESM assessment of Extraversion, which included outgoing and quiet).

Limitations and Future Directions

Although we believe our results are a critical first step for the application of idiographic network techniques in personality research, this study was limited in several ways. First, we

constructed idiographic networks using VAR models based on nine behaviors from the BFI that correspond to four of the Big 5. There is little reason to believe that these networks capture the full space of behaviors through which personality manifests. Indeed, individuals may manifest the same traits differently (Nesselroade & Molenaar, 2016), which indicates the necessity of assessing a broader range of behaviors. Moreover, although the centrality estimates appeared more stable than estimates of individual edges (i.e. model terms), there is also little reason to assume that these terms capture how traits manifest or capture meaningful psychological variability (Hallquist & Hillary, 2018).

Second, given weak lagged network consistency and strong contemporaneous consistency, it is unclear what the correct time lag between assessments of personality should be, as there has been little research investigating the psychometric properties of ESM (Beck & Jackson, 2019a; see Wright & Zimmerman, 2018 for an exception). That is, at present, no research has addressed how the measurement interval between ESM assessment points affects the contingent, lagged measurements between them. However, to best utilize and understand the utility of time-series models in personality, such a question must be answered. Indeed, there is little reason to expect strong predictive relationships between behaviors that occur four hours apart (Epskamp et al., 2018), as we have in the current study. The weak, non-zero associations between behaviors across time points suggest some contingency between behaviors but the range of stability of the idiographic networks suggest that the nature of those contingencies differs substantially across people.

Third, with only two time points across two years, it is impossible to discern long-term patterns of change. While many personality development studies utilize this time frame (e.g. Watson & Humrichouse, 2006), future research examining longitudinal personality networks over longer time periods are needed. As it is, there are several open questions, including whether

patterns of network consistency are similar to traditional nomothetic patterns of consistency, which tend to exhibit nonlinear decay over time that asymptotes at a nonzero value (Fraley & Roberts, 2005).

Fourth, using a college-aged sample makes it difficult to disentangle how age-graded social roles may impact observed trajectories of personality development (e.g. Roberts & Jackson, 2008). Indeed, as noted previously, college students' schedules tend to change each semester, which could impact the consistency of lagged network patterns. Working adults' schedules, in contrast, may be more stable (e.g. most adults do not start new jobs twice per year), leading to stronger consistency of lagged network patterns. In other words, the consistency observed in this sample offers a conservative estimate of what may be expected in other samples.

Fifth, our sample was potentially limited in size in terms of the number of ESM assessments per person. To account for the limited number of assessments for each person as well as variability in how often they did respond, we used a smaller range of regularization tuning parameters and also tested regularization tuning parameters scaled to the sample size (Epskamp 2016b; Epskamp & Fried, 2018). However, even though we chose our parameters carefully, this still raises two issues. For those participants with fewer numbers of observations, scaled parameters do not rule out specific life events or personality characteristics that may have caused participants to respond less often. Larger datasets are needed to test these moderation questions. Second, we used regularization for edge and model selection. Regularization techniques impose a penalty that tends to result in smaller regression weights (often called "weight decay"), and the penalty is non-linearly and negatively related to sample size. Particularly for the lagged responses, this might result in much smaller weights in waves in which participants had fewer responses than in the other. Different weight magnitudes across waves may account for some of the negative consistency estimates we observed. Moreover,

fewer responses limit the reliability of idiographic models and may partially explain why estimates of idiographic reliability were much lower than nomothetic reliability. Indeed, the maximum number of potential responses (59) in this study only modestly exceeds the minimum recommended threshold for such idiographic time-series analyses (50; Epskamp, Waldorp, et al., 2018), and the case was by definition, worse for the split-half models we used to assess reliability. As such, the reliability estimates, particularly of the lagged networks that include more predictors, likely partly reflect low power.¹⁵

Conclusion

Idiographic networks allow researchers to address a number of novel personality questions. The present study demonstrated the utility of idiographic time-series networks of personality to inform the structure and development of personality. In capturing important overall patterns of behavior, between-person models of personality fail to capture the complexity of individuals. The typical finding of longitudinal personality studies is that personality is relatively stable. The current study suggests that this conclusion is too general, with nomothetic models glossing over meaningful change. At an idiographic level, personality is both very stable and very unstable, depending on the person and the time lag. The reason for these vast differences in stability should be further investigated at an idiographic level.

¹⁵ We also tested how sample size related to consistency estimates, testing both whether the number of observations in a given wave or the difference in number of observations between waves were associated with ipsative contemporaneous and lagged consistency. These were almost weakly correlated at best and did not vary as a function of the type of model (see the section titled “Validity Check: What Are the Methodological Correlates of Consistency?” in the online materials on the OSF and GitHub).

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Table 1

Item Text and Descriptive Statistics of ESM Items for Waves 1 and 2

Name	Item Text	Wave 1		Wave 2	
		M	SD	M	SD
Kind (A)	How 'considerate, kind' were you?	3.42	0.61	3.40	0.65
Rude (A)	How rude were you?	1.47	0.38	1.50	0.41
Lazy (C)	How lazy were you?	2.37	0.53	2.32	0.55
Reliable (C)	How reliable were you?	3.76	0.56	3.77	0.54
Outgoing (E)	How 'outgoing, sociable' were you?	3.03	0.49	2.92	0.53
Quiet (E)	How quiet were you?	3.01	0.44	3.10	0.46
Depressed (N)	Did you feel 'depressed, blue'?	1.62	0.53	1.56	0.45
Relaxed (N)	How relaxed were you?	3.42	0.50	3.32	0.51
Worried (N)	How worried were you?	2.26	0.60	2.29	0.57

Note: Each of the ESM items was preceded by the phrase “During the last hour,…”

Table 2

Descriptive Statistics of Rank-Order Correlations Across Types of Idiographic Models

	Contemporaneous					Lagged				
	M	SD	Med	Min	Max	M	SD	Med	Min	Max
$\lambda = .025-.25$ (main analysis)	0.09	0.10	0.06	-0.10	0.33	0.01	0.10	0.01	-0.23	0.31
$\lambda = .025-.5$ (stricter penalization)	0.09	0.12	0.06	-0.14	0.37	-0.01	0.10	-0.01	-0.21	0.25
$\lambda = .01n$ (scaled penalization)	0.09	0.13	0.10	-0.21	0.40	0.01	0.10	0.00	-0.25	0.31
$\lambda = 0$ (unregularized)	0.03	0.11	0.05	-0.14	0.32	0.01	0.11	0.00	-0.22	0.25
Bivariate Associations	0.17	0.11	0.14	-0.06	0.44	-0.01	0.09	-0.01	-0.20	0.21
P-Factor Analysis	0.05	0.12	0.10	-0.14	0.17	0.08	0.05	0.09	0.01	0.16
Empirical Bayes	0.12	0.12	0.11	-0.11	0.44	0.03	0.09	0.03	-0.21	0.25
GIMME	0.04	0.12	0.04	0.20	0.33	-0.02	0.10	0.00	0.36	0.23

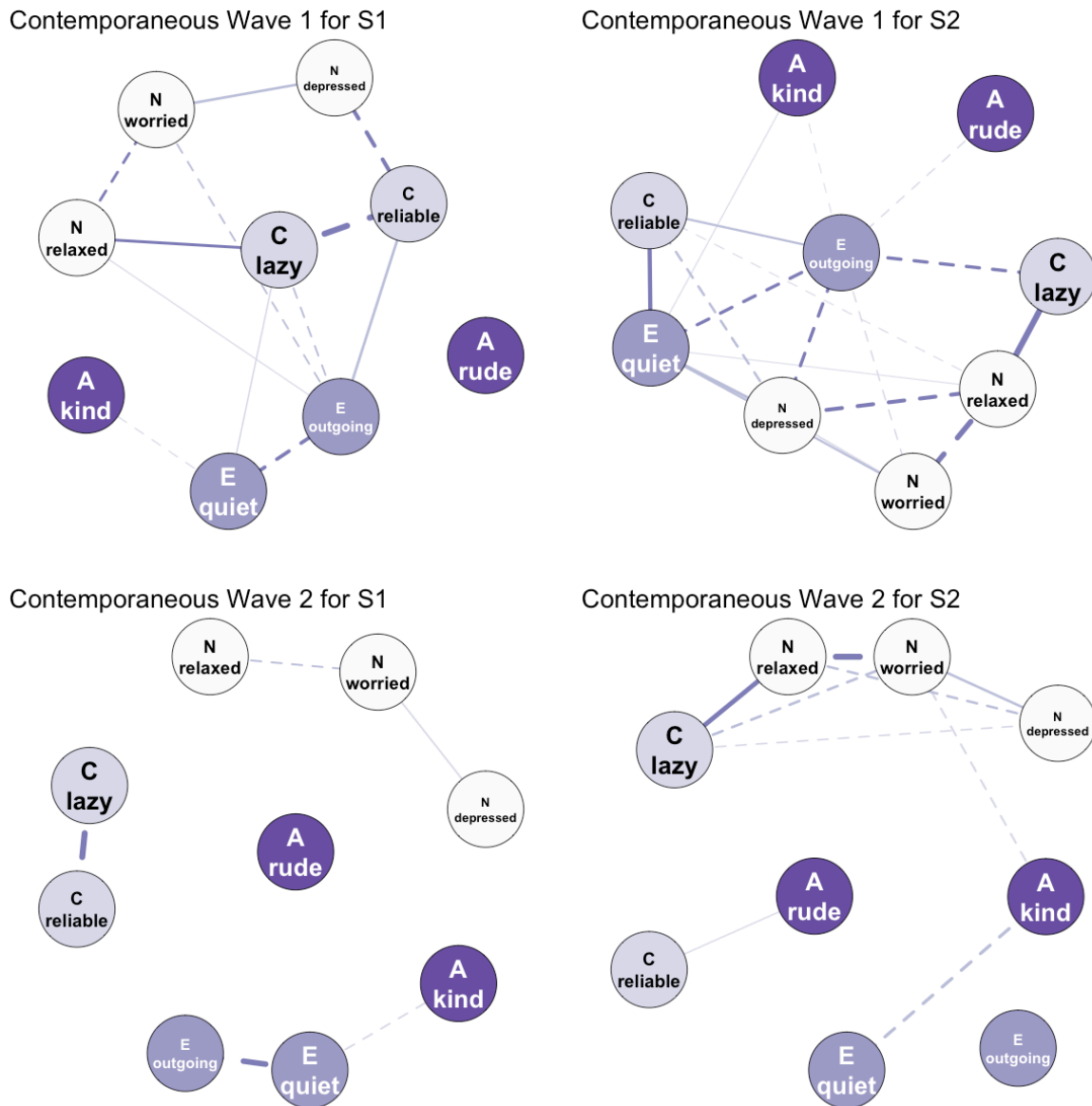


Figure 1. Idiographic contemporaneous personality networks for example Subjects 1 and 2 in wave 1 (top row) and wave 2 (bottom row). All contemporaneous networks represent within-time point relationships between indicators, controlling for cross-time point patterns. The different node colors indicate the putative Big 5 factor to which each item belongs. Solid lines are positively signed edges, while dashed lines are negatively signed edges.

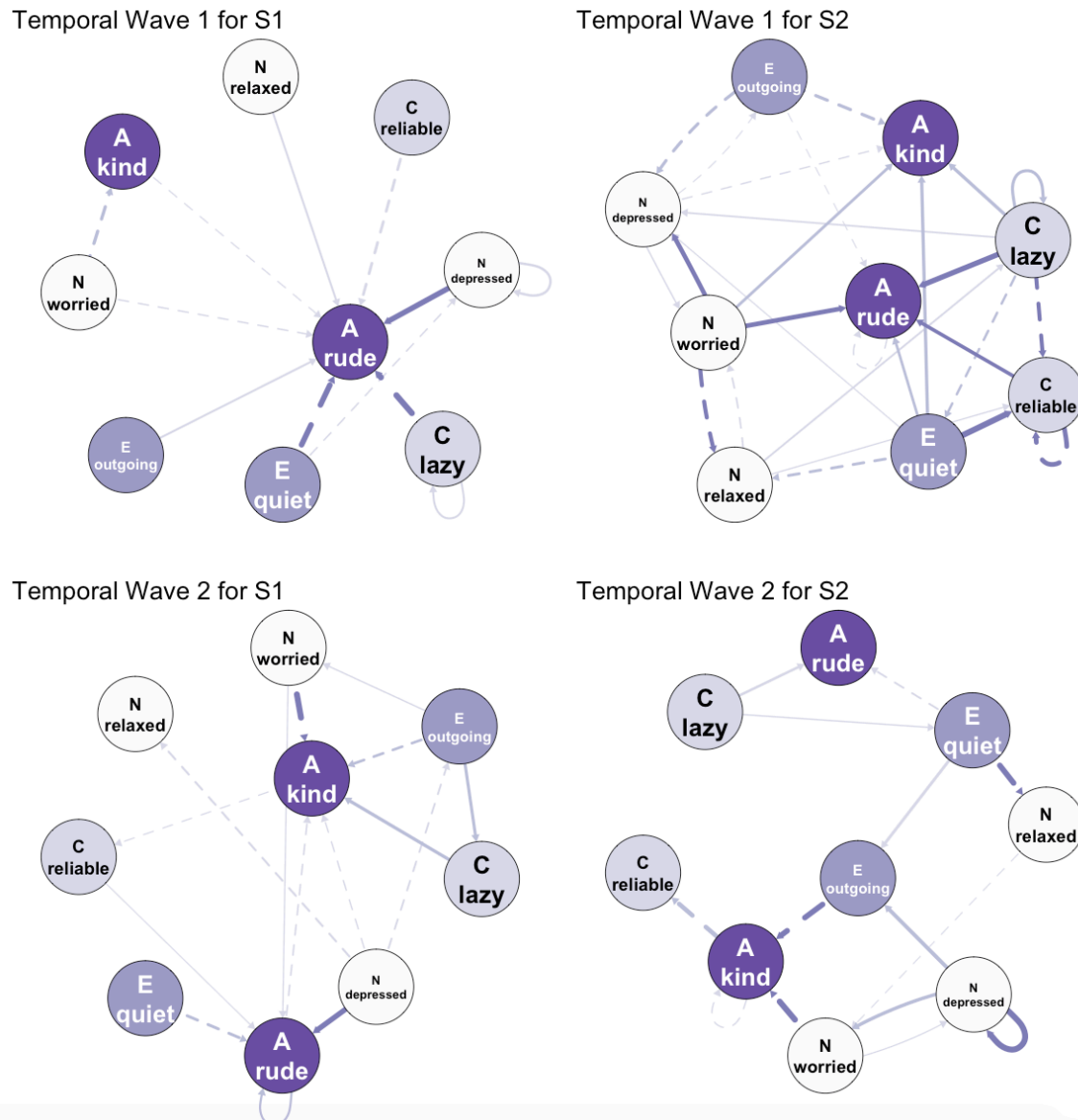


Figure 2. Idiographic lagged personality networks for example Subjects 1 and 2 in wave 1 (top row) and wave 2 (bottom row). All lagged network models index lag 1 autoregressive relationships between indicators. The different node colors indicate the putative Big 5 factor to which each item belongs. Solid lines are positively signed edges, while dashed lines are negatively signed edges.

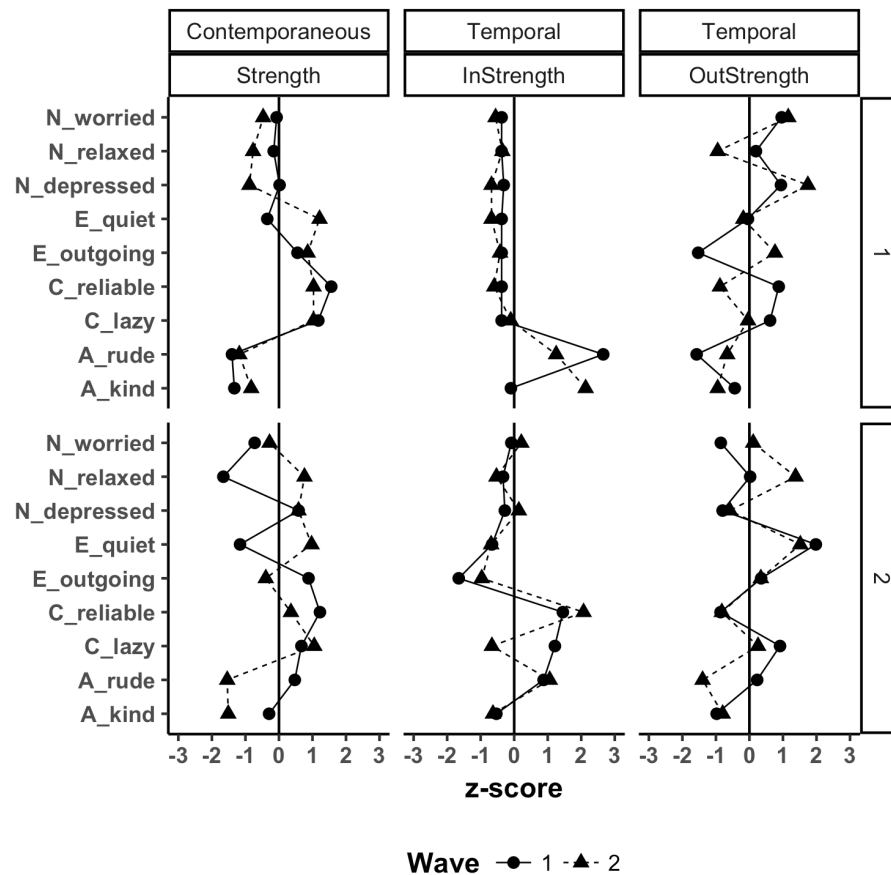


Figure 3. Centrality indices of example Subjects 1 and 2's lagged and contemporaneous networks across waves. All indices have been z-scored within network type (contemporaneous, lagged), wave (1, 2), and measure to allow for comparisons across waves and measures.

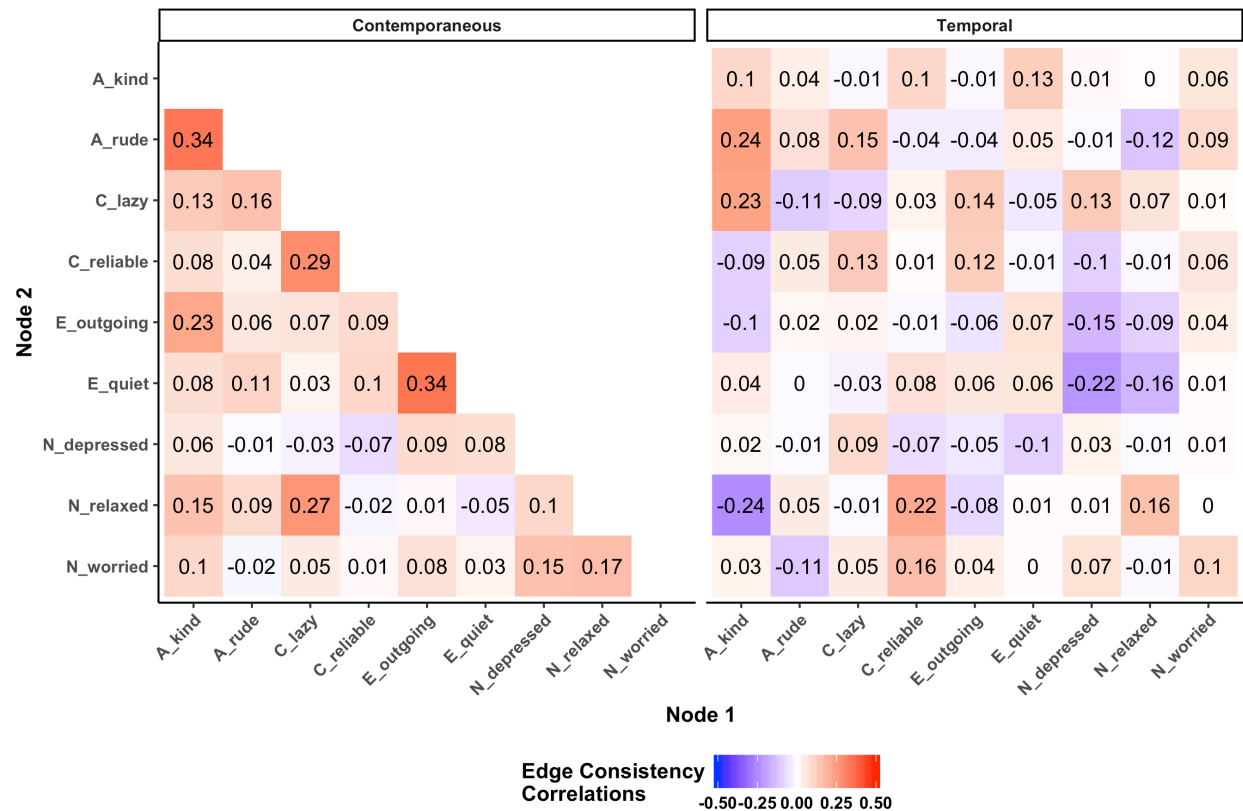


Figure 4. Rank-order stability of edge weights across waves for contemporaneous (left) and lagged (right) idiographic networks. Contemporaneous networks are symmetric, so only the lower triangle of the matrix of rank-order correlations is shown. Lagged networks are not symmetric, so the relationships are represented as Node 1 → Node 2. Rank-order consistency indexes interindividual differences in the consistency of edge weights across individuals for each edge.

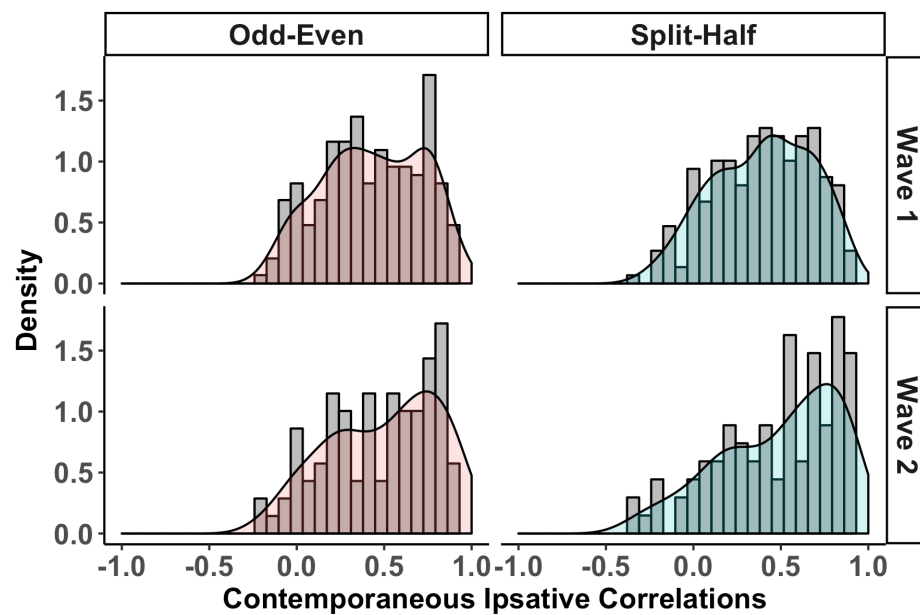


Figure 5. Density of contemporaneous ipsative (profile) split-half and odd-even reliability of idiographic networks across waves with a kernel density overlay. The left panels present the stability of relationships between odd-only and even-only network relationships, while the right panels present the stability of network relationships between the first and second weeks of responses. The top panels display consistency in the first wave, while the bottom panels display the second wave.

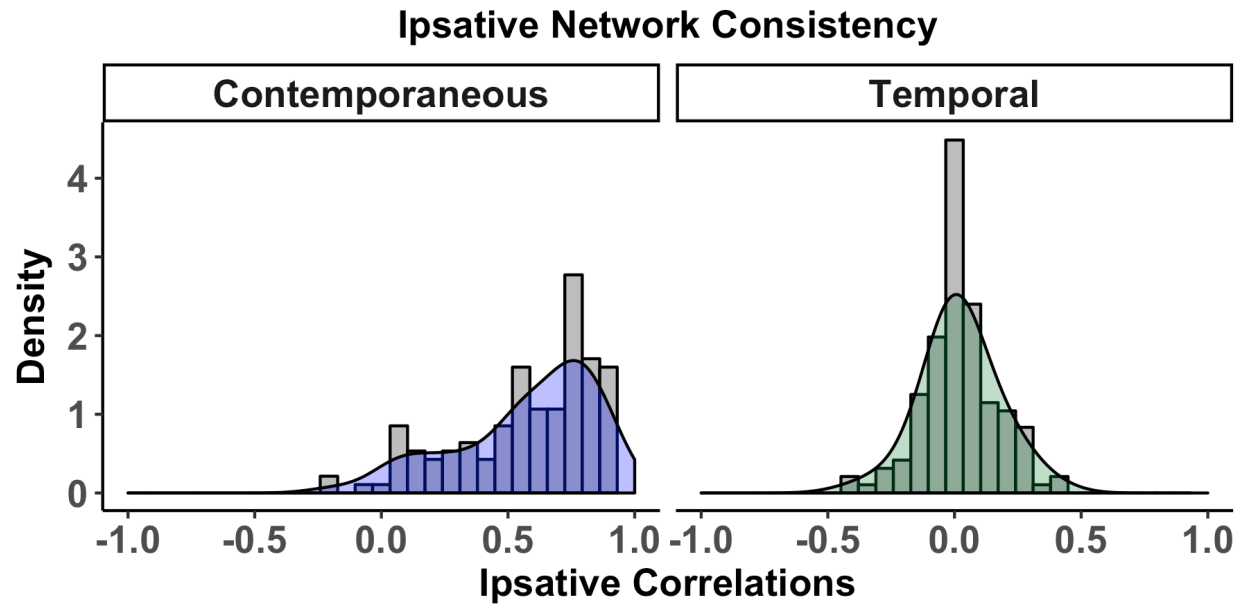


Figure 6. Density histogram of ipsative (profile) stability of idiographic networks across waves. Overlay represents the kernel density. the left panel presents the stability of the contemporaneous relationships, while the right panel presents the stability of lagged lag 1 autoregressive relationships.

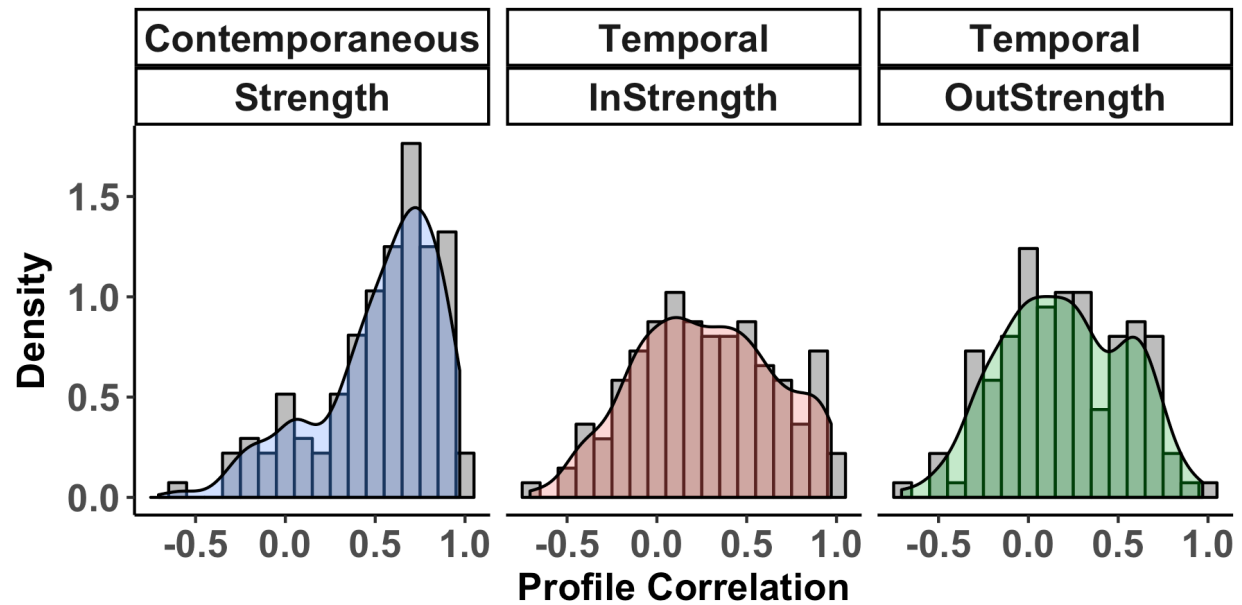


Figure 7. Density histogram of ipsative (profile) stability of centrality indices of idiographic networks across waves with a kernel density overlay. The middle and right panels represent the stability of lagged lag 1 autoregressive network relationships, while the left panel presents the stability of the contemporaneous network relationships.

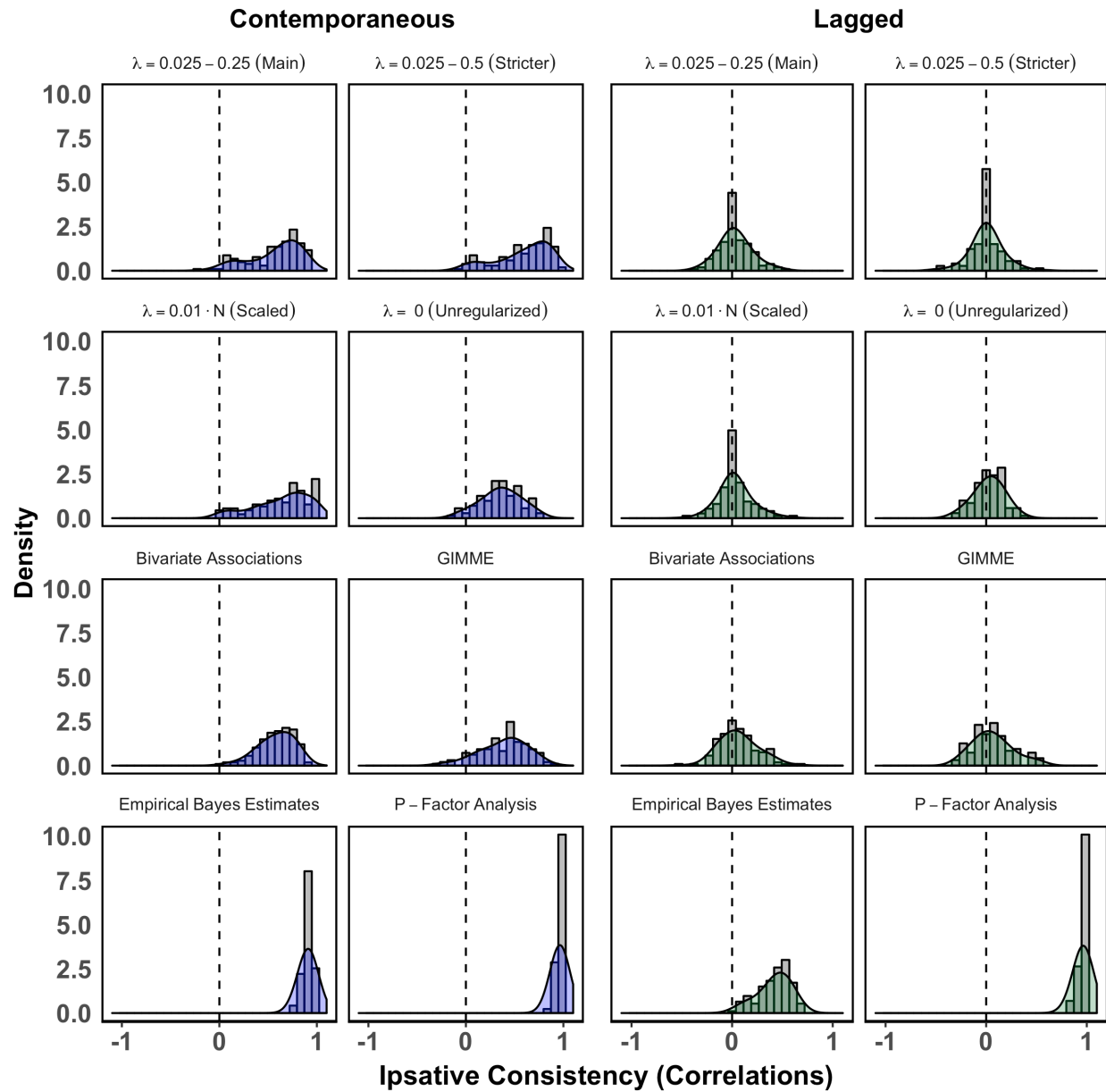


Figure 8. Density histogram of ipsative (profile) stability of idiographic networks across waves for different idiographic models. Overlay represents the kernel density. The left panel presents the consistency of the contemporaneous relationships, while the right panel presents the consistency of lagged lag 1 autoregressive relationships.