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Abstract

Privacy calculus is a well-researched model for predicting information disclosures. In a privacy calculus framework, consumers exchange their personal information to receive some benefit(s). However, a consumer's initial information disclosure decision often does not appear to be a simple cost-benefit calculation. For example, an account registration process may require the exchange of a great deal of personal information for seemingly small initial benefits. Perhaps the consumer is initially "oversharing" because they intend to gain much more benefit in the future; essentially, committing to a long-term relationship with the provider. To account for additional variance in such scenarios, we draw from commitment-trust theory; core marketing literature on consumer-provider relationships that helps explain the role of consumers' desire for relationships with providers. We test our model using a field experiment methodology with a sample consisting of 1,047 university students and adults over the age of 30. Our results indicate that consumers' anticipated relationship commitment to a service provider better explains their initial information disclosure when registering to use a mobile app than a traditional cost-benefit privacy calculus alone.

1. Introduction

Consumer information disclosure—particularly through information technology—has become a popular topic of research because of the great potential for both value creation and information privacy concerns (Bélanger & Crossler, 2011; Norberg, Horne, & Horne, 2007; Smith, Dinev, & Xu, 2011). Given the rate of consumer adoption of the latest technologies that combine personal information in valuable ways with an apparent disregard for disclosure risks (Acquisti, Taylor, & Wagman, 2016; Gross & Acquisti, 2005), researchers have increasingly focused on the question: *Why do* *consumers appear to readily disclose considerable personal information for seemingly small or insignificant benefits?*

Extant research addressing this question has presented several useful theoretical models. Most commonly (Wirth, 2018), consumers are framed as rational decision makers who evaluate the tradeoff between information disclosure costs and benefits (Culnan & Armstrong, 1999; Dinev & Hart, 2006; Kehr, Kowatsch, Wentzel, & Fleisch, 2015). However, many have argued that consumer decisions are not completely rational because consumers cannot know the true nature of the privacy risks and are likely far more susceptible to exploitation because of asynchronous information (Acquisti & Grossklags, 2003, 2005; Kehr et al., 2015; Wilson & Valacich, 2012). Therefore, other perspectives like *principal-agent theory* have been used to explain information disclosure decisions in the presence of asynchronous information (Chipidza, Leidner, & Burleson, 2016; Pavlou, Liang, & Xue, 2007). However, just how asymmetric is the information about providers' intentions with consumer data? In 2020, a report by the Norwegian Consumer Council (NCC) found that 10 popular apps used for purposes like menstrual health tracking, online dating, beauty, religion, games, and keyboards were sharing user data with a least 135 unique third parties (Myrstad & Tjoestheim, 2021). In 2019, over 1,000 Android apps were found to be harvesting data even after being denied permissions (Reardon et al., 2019). In 2017, researchers discovered over 20,000 app pairings that were working together to leak sensitive consumer data. As early as 2010, researchers had discovered that over 30 percent of Android apps were leaking private data (Gibler, Crussell, Erickson, & Chen, 2012). These are just a fraction of the studies showing privacy problems with mobile apps and devices that have made worldwide headlines over the years. In other words, although the intentions of providers (e.g. mobile app companies) are still unknown at the time of transactions, consumers are not as naïve as they used to be. Yet consumers continue to download apps and give them permission to use much of the data on their devices for seemingly small initial benefits.

One logical, yet under-studied, explanation for this phenomenon is that consumers anticipate not only an initial benefit of the disclosure, but also the enjoyment of future benefits as part of a long-term relationship. Academic marketing research uses the well-established *commitment-trust theory* (Morgan & Hunt, 1994) to explain such relationships. We draw from this theory to enhance a core privacy calculus model (Culnan, 1993; Dinev & Hart, 2006) where the perceived risks and benefits of an initial disclosure decision (e.g. downloading a new mobile app), along with the consumer's desire to make a "relational commitment" to the provider, affects their initial information disclosure.

We utilized a unique experimental design intended to replicate real privacy risk fears and a real information disclosure scenario as a quasi-field experiment. This involved creating an actual mobile application and recruiting participants under the false pretense (with IRB approval) of a software company soliciting their participation in testing a "beta" version of a forthcoming mobile application ("app"). Participants had a choice between just testing the app with very little information sharing, or they could complete the app's registration process in exchange for full access to the future, mature version of the app. This replication of a commonly-used app testing process allowed the collection of a wide range of personal information. The process included a manipulation of provider communication to observe its impact on information sharing.

2. Theoretical Model -Privacy Calculus

2.1 Privacy Calculus

Perhaps the most prominent theory thus far used to evaluate personal information disclosures is *privacy calculus* (Dinev & Hart, 2006; Kehr et al., 2015; Laufer & Wolfe, 1977; Xu, Teo, Tan, & Agarwal, 2009). According to this theory, an individual confronted with a decision to share or retain personal information in exchange for some benefit(s) performs a complex comparison of the decision's perceived risks and benefits, choosing to share their information when the perceived benefits outweigh the perceived risks. The perceived benefits and risks associated with disclosure are context-dependent based on the specific disclosure scenario (e.g., mobile app, website, etc.). Figure 1 summarizes the theorized relationships:

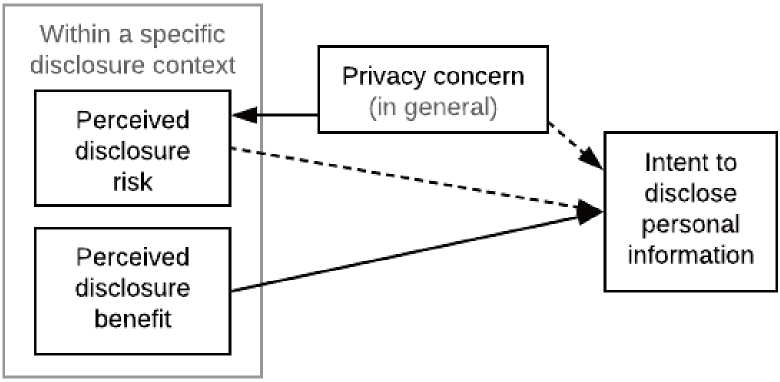

Figure 1 Summary of the theorized relationships

In privacy calculus, costs are operationalized as the risk that the personal information required to achieve the benefits offered by the service will be compromised (Dinev & Hart, 2006). Both perceived risk and disclosure intentions are affected by the consumer's privacy concern, which is a general perception of concerns that personal information will be misused (Smith, Milberg, & Burke, 1996).

Research based on privacy calculus has primarily been limited to the prediction of an information disclosure in the context of a single transaction (Dinev & Hart, 2006; Kehr et al., 2015; Xu et al., 2009). Although this is useful in many contexts, it has limited explanatory power for predicting information disclosures in a long-term context where the consumer expects to execute multiple transactions over an extended period with a lengthy time horizon before a net positive benefit is anticipated. Therefore, while we begin the core of our theoretical model on privacy calculus theory, we augment it with additional theory to explain long-term expectations.

2.2 Commitment-Trust Theory

Commitment-trust theory is widely used for describing key factors that govern sequential exchanges between persons and organizations (Cook & Emerson, 1978; Morgan & Hunt, 1994). "We conceive commitment between exchange partners to be an interpersonal attachment leading persons to exchange repeatedly with the same partners" (Cook & Emerson, 1978). In the privacy context, the "partners" involved in the relationship are the consumer and the mobile app provider. Commitment-trust theory posits that a consumer's commitment to a relationship with a provider describes a cost-benefit trade-off similar to privacy calculus as well as more social outcomes such as relationship commitment, cooperation, and in our case, the decision to acquiesce, or agree, to the mobile app provider's request for the consumer's personal information (Morgan & Hunt, 1994). Prior research shows that consumers have an initial reluctance to share information but acquiesce when required to receive some benefit – known as the "Privacy Paradox" (Kokolakis, 2017; Norberg et al., 2007; Wilson & Valacich, 2012). The focal construct of commitment-trust theory is *relationship commitment* which represents a consumer's willingness and expectation to engage in both a depth and breadth of transactions with the provider over time (Morgan & Hunt, 1994). It is important to note that relationship commitment represents a consumer's perception at a specific point in time and indicates not their actual, but their expected, engagement for the future—thus, making it a useful construct to explain consumer information disclosed at initial app adoption.

At first glance, relationship commitment may seem similar to the *intent to adopt* construct from technology acceptance theory (Davis, 1989) or the *intent to disclose* construct from privacy calculus theory (Dinev & Hart, 2006) which represents a consumer's intention to disclose their personal information to a provider. While information disclosure intention is one indication of relationship commitment, it is not the only indicator. For example, relationship commitment signals a desire not only for an initial transaction, but an ongoing relational exchange where the consumer feels they can co-create value with the provider by sharing personal information and receiving increasingly personalized value over time (Gundlach, Achrol, & Mentzer, 1995; Saarijärvi, Kannan, & Kuusela, 2013). Therefore, the measurement items for relational commitment refer not only to initial disclosure intentions, but also to a commitment to use the provider's service as it is intended.

Relationship commitment is relevant, in part, because providers to do not generally share their consumer data with competitors. For example, downloading the popular app Hiya™ exposes a consumer's contact list and location data to the provider for the benefit of caller ID and blocking. Those consumers would be less likely to also download the similar app Truecaller™ (or vice versa) since doing so would only add additional information exposure without any added benefit since the utility is the same. In other words, the consumer has decided to form a relationship with Hiya which they are less likely to form with Truecaller to maintain an optimal risk/benefit calculus. However, a consumer may also try out both apps initially to see which one offers the most utility of the type they are looking for (call blocking and identification). They will have to initially give both providers full location and contact data. However, consumers are likely to delete one of them eventually and that initial disclosure becomes less valuable over time as the consumers' contact list and location data is updated. While perceived costs and benefits of the relational commitment are key antecedents, the most distinguishing antecedent of commitment-trust theory may be the expanded conceptualization of trust. For example, privacy calculus theory conceptualizes trust more narrowly in scope as the belief that the provider will not behave unethically with consumer data (Dinev & Hart, 2006).

In commitment-trust theory, trust is defined as "a willingness to rely on an exchange partner in whom one has confidence" (Moorman, Zaltman, & Deshpande, 1992). This conceptualization aligns with that of *institution-based trust* referring to an individual's trust in the institutional environment in which a transaction is relevant (McKnight, Choudhury, & Kacmar, 2002). Institution-based trust accounts for the consumer's trust in the structural elements of the relationship; interpreted as the policies, procedures, and technologies designed to maintain the security and privacy of the consumer's personal information. The measurement items used by Morgan and Hunt (1994)—which are also adapted for this research—represent all three of the major components of institution-based trust as defined by McKnight et al. (2002) including the provider's competence, benevolence, and integrity. Also, according to commitment-trust theory, *communication* is a key antecedent of trust. Communication is considered in privacy calculus theory but is highly relevant to electronic information disclosure. It is broadly defined as, "the formal as well as informal sharing of meaningful and timely information" (Anderson & Narus, 1990). Communication leads to trust by setting expectations, aligning perceptions, and resolving disputes (Etgar, 1979). This is relevant to this research context because most electronic information disclosure scenarios involve communication between the information service provider and the user in the form of an end-user license agreement (EULA) or "privacy policy" (Flavián & Guinalíu, 2006). The EULA's and privacy policies are some of the primary methods by which providers declare exactly which forms of information will be collected and how information will be stored, shared, and destroyed. As providers disclose more information about their collection practices, communication is improved, and trust in the provider increases (Keith, Frederickson, Reeves, & Babb, 2018; Wu, Huang, Yen, & Popova, 2012).

2.3 Proposed Theoretical Model

Figure 2 illustrates our proposed theoretical model based on privacy calculus, augmented by commitment-trust theory (Morgan & Hunt, 1994), and slightly modified for the mobile app context. The negative relationship between privacy concern and disclosure decisions has been repeatedly demonstrated in prior privacy studies (Baruh, Secinti, & Cemalcilar, 2017; Bélanger & Crossler, 2011; Dinev & Hart, 2006; Malhotra, Kim, & Agarwal, 2004). Therefore, this theoretical model includes the relationship between privacy concern and disclosure decisions only as a control variable to isolate this observed source of variance.

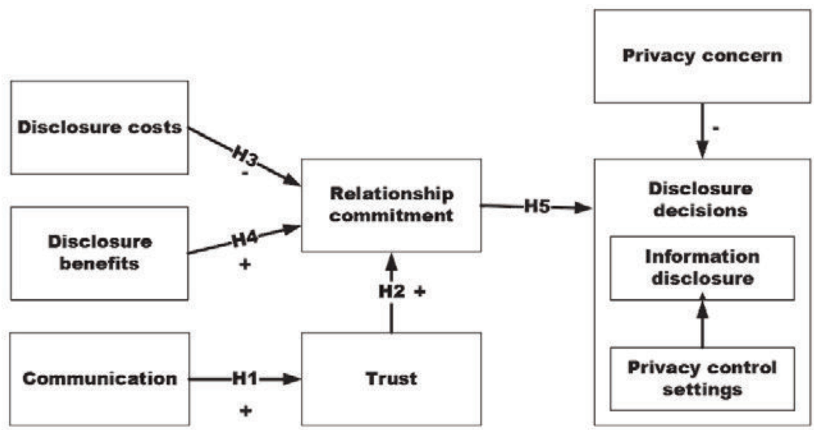

Figure 2 – Proposed Theoretical Model

2.4 Hypotheses

Communication is an important aspect of social exchange (Altman, 1975; Cook & Emerson, 1978; Morgan & Hunt, 1994). According to one publication (Thibaut & Kelley, 1959), "…as the attitudes of persons A and B toward one another become more favorable, communication between A and B becomes more frequent; and, conversely, as the rate of communication between A and B increases, attitudes toward one another become more favorable" Communication in a customer relationship environment, such as the provider consumer dyad, consists of an information exchange intended to provide mutual benefit. In this study, the mobile app provider informs the consumer of the features and potential benefits that come from using the app. The provider also presents a usage agreement explaining the terms of service, and the consumer communicates their acceptance of these terms. In previous studies, communication of a privacy policy increased participants' level of trust (Wu et al., 2012). The consumer's response includes the personal and location information they share with the provider to enable the app on the consumer's mobile computing device.

H1: Mobile app provider communication in the form of privacy policies or EULAs will increase a consumer's trust in that provider.

Without trust, little or no social exchange can be expected (Blau, 2017). The mobile app context is a nascent area for trust and privacy research. If the mobile app user believes in the competence, benevolence, and integrity of the provider (McKnight et al., 2002), they will be more willing to disclose data and, thus, intend to do so over time—thus, increasing relational commitment (Lin & Wang, 2006; Park, Lee, Lee, & Truex, 2012; Sargeant & Lee, 2004; N. Sharma & Patterson, 1999).

H2: Trust in a mobile app provider will lead to increased levels of relationship commitment to that provider.

In cost-benefit based decision models, perceived negative factors are described as the perceived risks of disclosing personal information. In prior research, (Ravald & Grönroos, 1996) it was posited, but the proposition not tested, that consumer-provider dyads entail indirect costs - "psychological costs are the cognitive effort, the need to worry about whether a supplier will fulfil his promises" (page 26). In line with the Morgan and Hunt (1994) model of commitment-trust, costs are expected to reduce relationship commitment (Deng, Lu, Wei, & Zhang, 2010; Ravald & Grönroos, 1996).

H3: Perceived disclosure costs will decrease a consumer's relationship commitment to a mobile app provider.

Mobile apps provide a wide variety of known benefits to consumers which are contingent on personalization based on the consumer's data. Data concerning consumer location, relationships, shopping preferences, health and activity, and more have all been identified as utility-generating for mobile apps (Steinbart, Keith, & Babb, 2017). The realization of benefits expected from using mobile apps are predicted to increase the app user's relationship commitment to the provider (Casaló, Flavián, & Guinalíu, 2007; Ravald & Grönroos, 1996).

H4: Perceived disclosure benefits will increase a consumer's relationship commitment to a mobile app provider.

Relationship commitment is a personal attachment that can influence a user to engage in repeated transactions with the same partner. This is a form of uncertainty mitigation, which is understandable given the risky nature of the rapidly evolving mobile apps field. In prior studies, relationship commitment has led to information sharing in supply chains (Zhao, Huo, Flynn, & Yeung, 2008). Although relationship commitment also ebbs and flows over time, an initial positive exchange should indicate a future strengthening of the commitment. Mobile app users with high levels of relationship commitment are likely to disclose information with the expectation that doing so will generate future value.

H5: A consumer's relationship commitment to a mobile app provider will increase their actual information disclosure to that provider.

3. Methodology

3.1 Artifact – Smartphone App

One of the primary weaknesses of many information privacy and disclosure studies is that laboratory experiments are too often used (Bélanger & Crossler, 2011) which frequently do not represent the true risk/benefit perceptions that affect disclosure decisions. To test our theoretical model, it was important to generate the potential for real risk and benefit perceptions among the participants. To accomplish this objective, we created a mobile app called *Sharing Tree*. With Internal Review Board (IRB) approval, we recruited participants under the false premise that a local mobile app development company needed their feedback on a forthcoming mobile app in the "alpha" version. The participants tested the app and then answered a series of survey questions.

3.2 Smartphone App Testing Procedures

Sharing Tree was created to be an "intelligent" local "finds" app that assisted the consumer in locating shopping deals, activities (e.g. concerts), and various entertainment options that would be predicted for the user based on their social network data, location data, and personal preferences determined by their usage history and personal data. In particular, the app would make recommendations to the user based on a predictive statistical model so that the utility of the recommendations improved as the consumer disclosed increasing amounts of information (including their social network, location data, and demographic information). Figure 3 depicts various screenshots from the app.


AT&T
2:13 PM
99 %
Map
Satellite
Your brother John
found 60% off
at the Gap
today at 12:35 pm.
What are you looking for?
Common categories
Clothing | Restaurants
Activities | Gasoline


AT&T
2:13 PM
99 %
PROFILE:
John Doe
Male
Age 22
Lives in
Payment profiles: Card number Expiration CVV2
Visa ****2231 10/13 **1
American Express ****8485 04/15 **7
Local Friends: click to view their profile
Sarah A. Greg B. Jonathon C. Kirstin D.
Jeffrey L. Katie M. Eric N. Madeline P.
Daniel T. Angela U. Pradeep V. Antonio W.
Import more from
facebook
REGISTER HERE FOR FREE

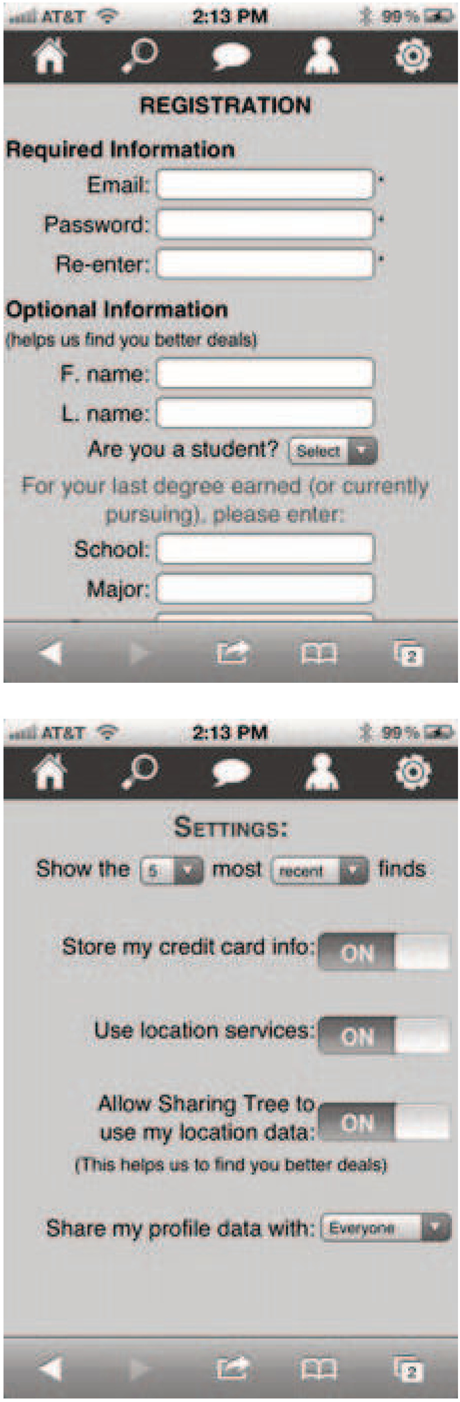

Figure 3 – Screenshots from the smartphone app

The app was developed in a “beta” version which allowed participants to test out these features in a “trial mode”—meaning the app gave them recommendations for a hypothetical user. After the participant had tested out the primary features of the app, they were presented with a registration page and offered the full “paid” version of the release version of the app at no cost if they chose to register immediately. This offer was framed as a reward to the participant for providing feedback to the mobile app developer about their impressions of the app. The amount of registration information provided by the participant—including the amount of the “optional” profile information disclosed—is the first of two dependent variables of this study. After the participant made their registration decision, they were asked to adjust the privacy controls to their preferences (the 2nd dependent variable). This ordering (first disclosure, then privacy controls) mimics the actual process followed when consumers adopt a mobile app; they must register before having access to the privacy controls. Figure 3 depicts the mobile app. As compared to scenario-based or other research methods, this information systems artifact created a context for real perceived risks from the service provider in several ways. First, the app clearly needed access to the consumer’s location data to provide the map of “finds.” Second, the app also made use of an online social network by allowing social network contacts to view each other’s finds and claiming that it used the usage history of social network contacts in the consumer’s own predicted recommendations. Third, the app also allowed for storage of credit card information to facilitate mobile commerce. Lastly, participants believed that the app was the product of an unknown local app development company. They did not realize that their data was in the hands of researchers and would not be shared for commercial purposes.

After testing and evaluating the mobile app, participants were asked to provide the mobile app development company with their feedback. This included both the scale items measuring our theoretical model as well as open-ended qualitative questions about suggestions to improve the app to create a realistic feedback scenario. At the end of the survey, participants were notified that the entire set of procedures was part of a research experiment and there was no sharing of their data for commercial purposes. Next, we confirmed that extra credit for the student participants had been recorded and would not be rescinded.

3.3 Participants

The initial participants for the experiment were undergraduate students recruited from a large, public university in the southern United States. In addition to this convenience sample, we also implemented a snowball sample of relatives or friends of the participants over the age of 30, resulting in a bifurcated sample of nearly equal-sized halves: students versus their parents and other referrals over age 30. The use of local participants was necessary to implement a methodology using real locations that would generate legitimate perceptions of the benefits and costs of visiting and otherwise transacting with local businesses and attractions. In other words, this limited sample was a deliberate trade-off that allowed for the replication of a realistic field experiment as opposed to a laboratory experiment alone.

The Snowball Sampling Method (SSM) has an initial group of research participants refer their social contacts to the study. This can be helpful when the referred contacts may be difficult for the researchers to reach, particularly in cases where the research topic, such as privacy, may be sensitive in nature (Parker, Scott, & Geddes, 2019). Another use for SSM is reaching participants who are geographically dispersed, a key consideration for this study. Our intent was to obtain data from the younger, local subjects and from their older friends or family who were not local. To encourage participation, the research subjects were offered extra credit (or extra credit provided to the one who referred them) and a random drawing of gift cards. To improve the likelihood that the students' referrals would be over the age of 30, we instructed the students that the participant's location data would be collected through the app and that any referral of theirs who completed the procedures within 16 kilometers of the campus would not count toward their extra credit. This was verified through actual location data.

Increasing sample size is a technique for mitigating some of the selection bias inherent to SSM (Atkinson & Flint, 2001). In this study, nearly half of the 1,047 successfully collected research participations were from the geographically separated participants.

Given that most of the older research participants were connected either socially or as family, there are concerns that trust the younger participants had towards the mobile app's publisher could be transferred to the older participants. One of the most respected models of user acceptance of an information technology artifact is the Unified Theory of Acceptance and Use of Technology (UTAUT), (Venkatesh, Morris, Davis, & Davis, 2003). While the UTAUT model includes the independent variable Social Influence, its relationship to Behavioral Intention is moderated by gender, age, experience, and voluntariness of use. Additionally, researchers have found that a person's life stage significantly affects their mobile app adoption categories and quantity (Frey, Xu, & Ilic, 2017). In a systematic review of the role of social influence in technology adoption (Graf-Vlachy, Buhtz, & König, 2018), the most significant identified form of influence in 80 of the 113 studies was compliance-based. Given the ordinary dynamic of parents influencing their children's choices via compliance, this implies that the older set of study participants were not necessarily inclined to comply with the requests from the younger participants.

Another issue in this study is that the Sharing Tree mobile app's publisher did not have a brand name. As stated in one study, "New online brands have a substantial barrier to the initiation of transactions by consumers because they are relatively unknown in comparison to their established and known counterparts." (Delgado-Ballester & Hernández-Espallardo, 2008).

A total of 1,196 participants completed the entire set of procedures. However, 149 were removed for "straightlining" responses or other procedural violations resulting in a total of 1,047 properly completed procedures.

The overall average age of participants was 34 years. However, the average of all those below 30 years was 20 years, whereas the ages of those above 30 years averaged 49 years, indicating the majority of the older participants were parents of the student participants. Eighty-five percent of the participants were Caucasian, five percent were African American, six percent were Asian, and two percent were Hispanic. Males constituted 61 percent of the participants, and virtually all the participants were smartphone users with an average of 26–35 downloaded apps.

3.4 Manipulation

As reviewed above, one of the key independent variables in commitment-trust theory is the communication offered by service providers to their consumers. As providers share more about their intentions, they are able to align perceptions and expectations (Etgar, 1979), thereby fostering trust (Anderson & Narus, 1990). In the mobile app information privacy context, providers communicate their institution-based trustworthiness (competence, benevolence, and integrity) to their consumers through privacy statements, seals, and other assurances (McKnight et al., 2002) which are typically offered both in the app descriptions and within the app itself. Therefore, we manipulated the level of detail offered in a privacy statement that appeared before the participant could review any part of the mobile app. Participants were randomly assigned to one of the three treatments depicted in Figure 4 below.

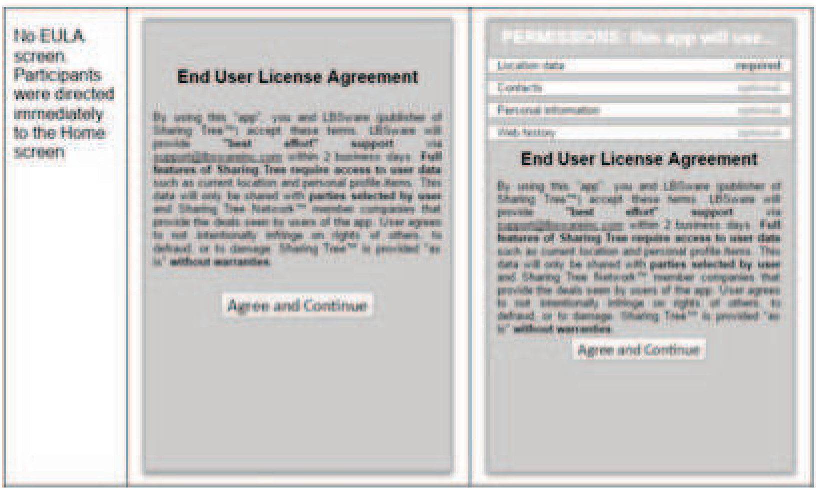

Figure 4 - Communication Manipulation

3.5 Measures

The primary dependent variable of this study was "information disclosure," measured by the percentage of requested fields disclosed by the participant. This was based on fields required to register (email and password) and the optional profile data (first name, last name, student status, university, major, degree, employment status, company, position, length of employment, address, city, state, zip, phone, gender, ethnicity, birth year, birth month, birthday, annual income, and relationship status). As a second measure of disclosure, we also calculated a score representing the selected privacy control settings across several controls: allow/disallow the use and storage of 1) location data, and 2) card data. The last privacy setting controlled

3) the sharing of user profile data with either everyone, friends only, or no one.

Where possible, scales from prior research were used to measure the independent variables. For example, the measurement scales of the reflective constructs relationship commitment, trust, and communication were all drawn from the original instruments (Morgan & Hunt, 1994). These scales and their corresponding reflective constructs have been well-established in prior studies and are appropriate for this study, albeit shifted to the context of an LBS app on a smartphone. However, to build upon prior research, we measured several types of both perceived disclosure costs and benefits that were relevant to the Sharing Tree context including: *utilitarian costs*, *social costs*, *privacy risk, utilitarian benefits*, *social benefits, locatability,* and *personalization*. These cost and benefit measures were systematically developed using an approach paralleling Smith et al (1996). First, high level constructs for the disclosure costs and disclosure benefits were proposed in line with a literature review of prior privacy studies. Focus group sessions were conducted with community groups as well as interviews with executives to help specify the domain and dimensionality of the proposed cost and benefit constructs. An expert panel was also consulted based on the literature review and material collected in the focus groups and interviews. It soon became clear that Disclosure Costs and Disclosure Benefits were higher order, formative constructs that would require the detailed development of first order, reflective constructs. For the Disclosure Costs, the first order reflective construct from prior literature was Privacy Cost (Xu, Luo, Carroll, & Rosson, 2011) and the first order reflective constructs developed through the focus group, interview, and expert panel process were Utility, Social, and Safety Costs. Together, these four first order constructs provided the facets forming the second order construct Disclosure Costs. For the Disclosure Benefits, the first order constructs that were yielded from the literature review process were Locatability, and Personalization Benefits (Xu et al., 2009) plus Utility and Social Benefits that were also manifest through the focus group, interview, and expert panel process. These four first order constructs together provided the facets defining the second order, formative construct Disclosure Benefits. Therefore, perceived Disclosure Costs and Disclosure Benefits were both modeled as first order, reflective sub-constructs with a second order formative factor similar to prior research on privacy concerns (Smith et al., 1996).

This combination of reflective and multi-ordered reflective/formative constructs was required in order to help develop a comprehensive understanding of these complex phenomena. Privacy and its correlates are some of the aspects of human nature that significantly define one's role and relationship to other humans in a society (Altman, 1975; Laufer & Wolfe, 1977).

The new measures developed through the focus groups, interviews, and expert panel were pilot tested using a prior data collection of 105 participants. The pilot data resulted in several minor changes to the newly created items measuring costs and benefits. Appendix A includes the items generated from the new measures.

General privacy concern is a known covariate of perceived privacy risk (Dinev & Hart, 2006). Therefore, *privacy concern for mobile apps* was measured based on an existing scale which includes the sub-constructs of *perceived surveillance*, *perceived intrusion*, and *secondary use* (Xu et al., 2011). In addition to the latent constructs reviewed above, we measured several covariates, including gender, age, ethnicity, education, and work experience.

4. Empirical Results

Before testing our hypotheses, we first performed pre-analyses to assess the validity of our measures and the success of our manipulation of the provider communication. Lastly, we conducted several post-hoc analyses to provide implications that are more thorough for practitioners.

4.1 Measurement Validity and Reliability

Although our theoretical model is based on prior tested theory (albeit in a different context), we have made significant adjustments to the measures for privacy costs and benefits. Therefore, we analyzed our model using partial least squares (PLS) based on the SmartPLS 3.2.4 software (Hair, Hult, Ringle, & Sarstedt, 2013) and followed recommended guidelines for PLS (Gefen & Straub, 2005; Lowry & Gaskin, 2014). PLS was further necessitated by our use of formative measures for privacy costs and benefits (Chin, Marcolin, & Newsted, 2003; Petter, 2018; C. Ringle, Wende, & Becker, 2015; C. M. Ringle, Wende, Sven, & Becker, Jan-Michael, 2015). One item was removed from the privacy concern scale (PCPS1) drawn from prior research

, and three of the new items created for this study (UTC3, SAC1, SOC2) were removed. The results based on the remaining items indicate acceptable reliability and validity. The complete results are in Appendix B. Perceived risks, perceived benefits, and privacy concern were each modelled as second order formative constructs with first order reflective sub-constructs. Therefore, following prior research (Benbasat & Wang, 2005; Jarvis, MacKenzie, & Podsakoff, 2003), we first analyzed the measurement properties of the reflective sub-constructs. We then replaced the scales for each sub-construct with their corresponding latent factor score as formative indicators of the second order formative construct. Although one sub-construct had minor measurement validation issues (utilitarian costs - UTC; see Appendix B for details), it was retained based on the content validity established by the qualitative interview (Diamantopoulos & Siguaw, 2006; Marakas, Johnson, & Clay, 2007).

4.2 Preventing and Testing Common Method Bias

Our methodology was designed with the intention of minimizing common methods bias (CMB). This was accomplished by establishing a different form of data collection for the dependent variables (the actual information disclosed through the app) than for the independent variables (survey items collected after the app was reviewed). Thus, the likelihood of CMB was reduced by *not* using a common method to collect data. In addition, data reflecting procedural violations were identified and removed from the results. We also examined the correlation matrix in Appendix B, Table B2 to ensure that all correlations between latent constructs were below 0.9. With the highest correlation being 0.705, and given different data collection methods, the evidence indicates that CMB has been minimized in this study.

4.3 Manipulation Check

As a manipulation check, we analyzed the difference among treatment groups on scale measures for perceived *communication*, perceived *privacy risk*, and *trust* in the provider. Table 1 summarizes the differences by treatment. Based on one-way analyses of variance (ANOVA), the communication treatment increased perceived communication, but only at the High condition. The High treatment also significantly reduced perceived risk over the Control and Low treatments. Interestingly, the Low treatment did not reduce perceived risk below the Control treatment. Lastly, the Low and High treatments marginally improved trust. Overall, we conclude that our manipulation affected participant perceptions.

Table 1. Manipulation Check								
Communication treatment	Means					p-values of ANOVAs		
	Communication	*Perceived risk*	*Trust*		Comparison	*Communication*	*Perceived risk*	*Trust*
Control (0)	4.95	4.18	4.20		**0 vs 1**	0.29	0.41	0.08
Low (1)	5.07	4.20	4.24		**1 vs 2**	0.20	0.00	0.18
High (2)	5.14	3.92	4.31		**0 vs 2**	0.02	0.00	0.06

Table 1 - Manipulation Check

4.4 Hypotheses Testing

Figure 5 visualizes the results of our hypotheses tests. The coefficients generated by the PLS algorithm are represented on the relationship lines between constructs, and the R-squared values on each construct represent the effect sizes. The *p*-values and *t*-statistics were generated using the bootstrap approach with 1,000 resamples. The R-squared value for our primary dependent variable, actual information disclosure, was 15.6 percent which is favorable for field experiments where consumer behaviors are the outcome measure (Kang & Shin, 2016; Keith, Babb, Lowry, Furner, & Abdullat, 2015; Zhang, 2015) as opposed to subjective, self-reported measures (Leom, Deegan, Martini, & Boland, 2021; S. Sharma & Crossler, 2014; Wang, Liao, & Yang, 2013; Yang, Gong, Zhang, Liu, & Lee, 2020) [e.g. Wang et al, 2013, pp. 66-68][1]. Each hypothesis of our commitment-trust model of information disclosure was supported, with the exception that, although relationship commitment did affect information disclosure, it did not affect the selected privacy control settings. The control variable *privacy concern* had a small, significant effect on disclosure.

[1] Studies of consumer behavior typically have low effect sizes (Peterson, Albaum, & Beltramini, 1985) due to the many factors that may influence actual decisions with real outcomes and implications as opposed to perceptions captured in surveys which are subject to common methods bias (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). For example, 84.7 percent of all consumer behavior studies reviewed by (Peterson et al., 1985) had effect sizes between 0.0 and 0.9 percent.

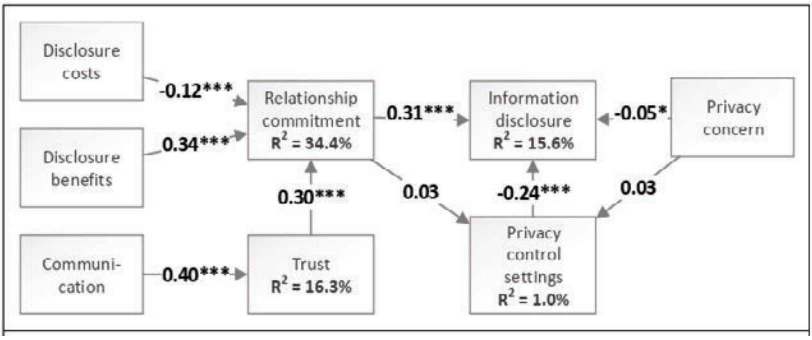

Figure 5 – Hypothesis Testing Results

4.5 Post-Hoc Analyses of Alternative Explanations of Observed Variance

As an additional contribution to both research and practice, we performed several post-hoc analyses to compare our model to prior research on privacy calculus along. We estimated three information disclosure models in addition to the proposed commitment-trust enhanced model above: 1) a traditional privacy calculus model *without* the expanded measures of costs and benefits contributed by our methodology, 2) a privacy calculus model *with* the specific cost-benefit measures, 3) the commitment-trust-enhanced model of privacy calculus in the present study, and 4) a combined model incorporating both privacy calculus and commitment trust relationships by adding direct relationships from disclosure risks and benefits to actual information disclosure (as opposed to being entirely mediated by relationship commitment) (Keith et al., 2015). Table 2 summarizes the R-squared values of information disclosure and relationship commitment as well as coefficients of the most relevant, comparable relationships of each model. The interaction effect from privacy calculus theory (Dinev & Hart, 2006) of *trust* with *disclosure privacy risk* was estimated using the product-indicator approach Chin et al. (2003).

Table 2. Model Comparison of R Squared Values				
Model:	Privacy calculus without expanded cost-benefit (1)	Privacy calculus with expanded cost-benefit (2)	Commitment-trust (3)	All combined (4)
Information disclosure (ID)	7.3%	11.4%	15.6%	16.0%
Relationship commitment (RC)	n/a	n/a	34.4%	37.6%
Relationship:	β			
Disclosure costs > RC			-0.12***	-0.12***
Disclosure benefits > RC			0.34***	0.34***
RC > ID			0.31***	0.28***
Disclosure privacy risk/costs* > ID	-0.01	-0.03		0.02
Disclosure benefits** > ID	0.09**	0.19**		0.08**
Trust * privacy risk > ID	-0.02	-0.02		0.00
Note: *In Model 1, this measure represents only the perceived privacy risk and no other forms of cost. In Model 2, it represents all expanded costs. **Model 1 includes both personalization and locatability benefits, but not utilitarian, social, or hedonic benefits. Model 2 includes all five.				

Table 2 - Model Comparison of R Squared Values

The R-squared value of the traditional privacy calculus model (1) was 7.3 percent. The second model (2) of privacy calculus parses out the contribution of our expanded measurement of costs and benefits. It resulted in an R-squared of 11.4 percent. After including the commitment-trust features theorized in this study, R-squared further improved to 15.6 percent. Therefore, the contribution of our model (*f*2) is 9.83 percent ((0.156 – 0.073) / (1 – 0.0156)) (Hair et al., 2013) which can be considered a "large" improvement over prior research (Cohen, 1969).

5. Discussion

Much of extant information privacy research has been focused on the cost-benefit tradeoff described by privacy calculus. Framing actual consumer information disclosure as a cost-benefit tradeoff mediated through relationship commitment found significant support in this study. Our results demonstrate strong support for a privacy calculus model enhanced by commitment-trust theory. Although a model combining privacy calculus and commitment-trust yielded a slightly higher R-squared value, the commitment-trust model alone provided a similar effect size with superior parsimony. All the core hypotheses were strongly supported. Communication (H1) fosters greater trust (β=0.40***), trust (H2) leads to relationship commitment (β=0.30***). Disclosure costs (H3) (β=-0.12***) and benefits (H4) (β=0.34***) also strongly affect relationship commitment, which affects information disclosure (H5) (β=0.31***). The control variable privacy concern had a significant negative impact on information disclosure (β=-0.05*), however it did not significantly impact privacy control settings (β=0.-03). The results indicate an expanded conceptualization of perceived costs and benefits is desirable not only in the commitment-trust model, but in privacy calculus models as well (4.1% R-squared improvement).

The context of this study was testing a working smartphone app with information disclosed by study participants in the Southeastern USA who chose to interact with the app. The results indicate that relationship commitment can be a significant determinant of user information disclosures. In (Dinev & Hart, 2006), the context of the study was a survey of a demographically broad sample also drawn from the Southeastern USA. A significant difference between these studies is the dependent variable in this study measured information disclosed. "Willingness to provide personal information to transact on the Internet" was the earlier dependent variable (Dinev & Hart, 2006). When combined with the major differences in the variables in each model, comparisons of statistical outcomes are difficult. For example, Dinev and Hart (2006) tested privacy concern as a mediator between perceived risk and willingness to provide personal information, finding a strong, negative correlation (-0.38**) between these variables. In contrast, this study used privacy concern as a control variable in its theoretical model and found a less significant negative influence (-0.05*) on information disclosure in the presence of relationship commitment. Some of this difference likely reflects the frequently observed "privacy paradox" – a low observed level of intent to disclose personal information, but high levels of actual information disclosure (Kokolakis, 2017; Norberg et al., 2007; Wilson & Valacich, 2012). Overall, the current study's results, as well as the post-hoc analyses, have several implications for research and practice.

5.1 Implications for Research

The study results suggest that examining the cost-benefit privacy calculus only for an individual transaction—without accounting for relationship commitment—provides an incomplete picture for decision-making. For example, in the post-hoc privacy calculus models in Table 2, when relationship commitment is included in the models explaining actual information disclosure, disclosure costs had no direct effect on actual information disclosure. There are two implications of these findings. First, researchers in future studies should account for consumers' consideration of establishing a long-term relationship with the information services provider. Second, methodologies that are entirely survey-based or that lack a specific disclosure context— and therefore lack the inclusion of actual information disclosure behavior—may only identify an effect of privacy concern on disclosure intentions. This could be the result of CMB or the fact that there is a known disconnect between disclosure intentions and actual behavior – the "privacy paradox" (Norberg et al., 2007). These results suggest that future research should account for relationship commitment and focus on actual behaviors rather than stated intentions, as recommended by Bélanger and Crossler (2011).

In their meta-analytical review (Baruh et al., 2017) of 166 privacy concern and privacy management studies conducted in 34 countries. They found that, "with respect to behavioral outcomes, users with higher privacy concerns shared less personal information…and utilized privacy protective measures more." (page 36). In line with these findings, privacy concern was found to have a statistically significant impact on information disclosure in the current study. However, no clear relationship was found between privacy concern and the privacy protective behavior of utilizing privacy controls.

5.2 Implications for Practice

For practitioners, a significant contribution of this study is the collection of consumer behavior through actual information disclosure instead of the much more common research approach of collecting consumer intent to disclose. There are several other more specific implications that are useful to practitioners. First, our manipulation of service provider communication produced important results. The difference in participant perceptions of *communication*, *privacy risk*, and *trust* were almost non-existent between the *control* group (no service provider communication) and the *low communication* group, which was operationalized as a EULA only (see Figure 4). These results empirically confirm what prior researchers have suggested (Cotton & Bolan, 2011) — that consumers ignore EULAs. However, the difference between the *low* and *high communication* groups was significant. The results suggest that for mobile app publishers, the addition of a simple list of data collected from the user (much like that offered on the Google Play™ platform) is an effective strategy to communicate to consumers and increase their trust. In contrast, the Apple App Store™ relies on individual pop-up requests, as each type of data is needed by an application. Perhaps Apple is relying, instead, on its brand credibility (Muñiz & O'Guinn, 2022) to assuage consumer fears and foster trust.

Another implication of this study's results for mobile app publishers is fostering relationship commitment can assist the publishers in customizing their apps, thereby increasing customer retention (Bojei, Julian, Wel, & Ahmed, 2013). The relationship marketing approach dovetails with the findings of this study regarding communication with mobile app consumers. Over time, mobile apps that evolve through a shared relationship between publisher and consumer may erect a barrier to competitors as switching costs increase along with relationship commitment (Palmatier, Dant, Grewal, & Evans, 2006).

5.3 Limitations and Future Research

Several limitations of this study present opportunities for future research. Although the results suggest that the relationship commitment construct captures consumers' long-term desires and intentions, it is not a measure of actual behavior over time. The proposed model is only a variance model. Future research should develop a process model of information disclosure and demonstrate how relationship commitment may be both increased by communication and decreased by ongoing data collection practices, data breaches, and other negative factors. The use of student participants and a snowball sample of their referrals over age 30 is a possible limitation of this study. Although this was a convenience sample, the qualitative results indicate that student participants were very similar to community groups. However, future research should further explore the factors that indicated the executives in our study yielded different outcomes from the students and community groups. A limitation of the SSM used in this study is some level of trust in the mobile app publisher may have transferred due to the close social relationships between the initial research subjects and the participants they referred to the study. This limitation may have been somewhat mitigated by the challenges faced by new brands in e-commerce.

The geographic scope of the research participants was entirely limited to residents of North America, especially the Southern states. Subsequent research adjusted for local cultural norms may isolate additional variance not possible within the scope of this study.

Another limitation of the study was the actual data collected during the registration process. Although the mobile app registration process was designed to mimic that of many possible apps, it may not have captured the data points considered sensitive by consumers.

Therefore, future research should also expand data collection to include other forms of data that may be considered more sensitive.

Lastly, although many forms of costs and benefits were identified in this study, not all of them were relevant in the mobile app context. Future research should specifically examine mobile apps with health and safety features.

5.4 Conclusions

The purpose of this study was to examine privacy trade-off decision-making using a commitment-trust based research model to validate the previously identified costs and benefits considered by decision makers in the mobile app context. A theoretical model consisting of reflective and formative constructs was empirically validated against a large cross-section of participants (n=1047). Our results suggest that understanding initial registration and disclosure decisions requires not only an expanded view of disclosure costs and benefits, but also a consideration of the consumer's long-term intentions to form a relationship with the mobile app provider. Furthermore, we find that the relationship commitment construct fully mediates the effect of perceived costs on disclosure decisions. In addition, without the collection of actual disclosure decisions, researchers may mistakenly identify an effect of disclosure privacy risk.

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Appendix A – Measurement Items

Table A.1. Measurement Items Created New For this Study	
Code	*Item*
UTB1	Mobile apps that use location data such as Sharing Tree can help me save time.
UTB2	Sharing Tree can help me spend less money for the same goods and service I use now.
UTB3	Sharing Tree should help me get more done than I could before it was available.
SOB1	Sharing Tree's location sharing will make me more accessible to my friends and family.
SOB2	Sharing Tree's communication features will make it easier to keep in touch with my friends and family.
SOB3	I can use Sharing Tree's location features to more easily get together in person with friends and family.
SOB4	Sharing Tree will help me by locating entertainments.
UTC1	Mobile apps with location features like Sharing Tree can be a waste of time.
UTC2	Mobile apps that use location services can consume more battery life than most apps.
UTC3	Using mobile apps like Sharing Tree can take up a lot of my attention.
UTC4	Mobile apps like Sharing Tree can consume a lot of my mobile device data plan.
SAC1	I am concerned that Sharing Tree might cause me to drive in an unsafe fashion.
SAC2	Using a mobile app like Sharing Tree could result in me seeing false advertising.
SAC3	Using a mobile app like Sharing Tree could result in me being the victim of a minor crime (e.g. petty theft, smartphone snatch-and-run).
SAC4	Using a mobile app like Sharing Tree could result in me being the victim of a serious crime (e.g. physical assault, burglary of home).
SOC1	I am concerned that using Sharing Tree would take my attention away from the people I am with at the time.
SOC2	I am concerned that Sharing Tree may interfere with the conversations I have with people close by.
SOC3	I am concerned that Sharing Tree could hurt my relationships with friends and family.
Note: the other measurement items used in this study were drawn from prior research with only slight modifications made for the Sharing Tree context	

Appendix B – Validation of Reflective Constructs

Validation of these items was based on current guidelines (MacKenzie, Podsakoff, & Podsakoff, 2011). As recommended, rather than testing the constructs specified as second-order formative (perceived costs, perceived benefits, privacy concern for mobile apps), we analyze the first-order reflective sub-constructs, which comprise the second-order formative constructs. This allows us to implement analyses that are appropriate for reflective constructs. First, we analyzed convergent and discriminant validity and reliability with a variety of analyses appropriate to latent reflective constructs (Fornell & Larcker, 1981). These measures are summarized in Tables B.1, B.2.1 B.2.2, B.3.1 and B.3.2. First, we examined the outer model weights to ensure that all were significant. This test was passed except for UTC4 ($p = 0.13$).

Table B.1 – Outer Model Weights			
Second order construct	First-order construct	Item	Outer weight
Privacy concern with mobile devices	Perceived surveillance	PCPS2	0.701***
		PCPS3	0.367**
	Perceived intrusion	PCPI1	0.288*
		PCPI2	0.400***
		PCPI3	0.408***
	Secondary use	PCSU1	0.527*
		PCSU3	0.542*
Perceived benefits of information disclosure through mobile devices – from prior research (Xu et al. 2009)	Locatability	LOC1	0.372***
		LOC2	0.379***
		LOC3	0.365***
	Personalization	PER1	0.321***
		PER2	0.382***
		PER3	0.414***
Perceived benefits of information disclosure through mobile devices – from pilot study	Utility benefits	UTB1	0.394***
		UTB2	0.336***
		UTB3	0.438***
	Social benefits	SOB1	0.312***
		SOB2	0.282***
		SOB3	0.313***
		SOB4	0.276***
Perceived costs of information disclosure through mobile devices – from pilot study. *Privacy costs (PRC) drawn from prior research and from pilot study.	Utility costs	UTC1	0.861***
		UTC2	0.207ǂ
		UTC4	0.145
	Safety costs	SAC2	0.496**
		SAC3	0.467*
		SAC4	0.297ǂ
	Social costs	SOC1	0.486ǂ
		SOC3	0.619*
	Privacy costs	PRC1	0.414***
		PRC2	0.407**
		PRC3	0.282*
	Communication	COM1	0.421***
		COM2	0.235*
		COM3	0.311***
		COM4	0.313**
	Trust	TRU1	0.242***
		TRU2	0.291***
		TRU3	0.197***
		TRU4	0.221***
		TRU5	0.220***
	Relational commitment	REL1	0.136***
		REL2	0.210***
		REL3	0.137***
		REL4	0.187***
		REL5	0.254***
		REL6	0.403***
Notes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, ǂ $p < 0.10$			

Next, all Cronbach's alpha and the composite reliability scores were above the recommended cut-offs (0.7 and 0.5 respectively) (Fornell & Larcker, 1981; Santos et al., 1999) with one minor exception. UTC was under the Cronbach's alpha (0.59) cut-off. Similarly, all constructs were under the cut-off for average variance extracted (0.50) except for UTC which was just barely under (0.47). Finally, the variance inflation factor (VIF) was calculated to test for violations of multicollinearity among independent variables. All scores were well below the 5.0 cut-off for reflective variables (Cenfetelli & Bassellier, 2009; Diamantopoulos & Siguaw, 2006). In summary, we conclude that the constructs have adequate reliability and convergent validity although we interpret UTC with some caution. Given the strong content validity of UTC, it is retained.

Table B.2.1 Validity and Reliability Criterion – part 1

	COM	LOC	PCPI	PCPS	PCSU	PER	PRC	Com rel.	α	VIF
COM	**0.602**	0.219	0.005	0.006	0.001	0.215	0.041	0.858	0.780	1.549
LOC	0.468	**0.803**	0.000	0.000	0.001	0.486	0.014	0.925	0.877	2.214
PCPI	-0.071	0.020	**0.829**	0.608	0.498	0.000	0.206	0.936	0.898	3.348
PCPS	-0.080	-0.005	0.780	**0.851**	0.392	0.000	0.163	0.920	0.841	2.657
PCSU	-0.026	0.023	0.705	0.626	**0.857**	0.000	0.178	0.933	0.857	2.217
PER	0.017	0.017	0.017	0.017	0.017	**0.876**	0.023	0.923	0.876	2.571
PRC	0.422	0.422	0.422	0.422	0.422	-0.151	**0.891**	0.931	0.891	1.812

Note: AVEs on diagonal; correlations below diagonal ; squared correlations above diagonal

Table B.2.2 Validity and Reliability Criterion – part 2

	REL	SAC	SOB	SOC	TRU	UTB	UTC	Com rel.	α	VIF
REL	**0.829**	0.028	0.224	0.000	0.436	0.273	0.126	0.868	0.829	2.278
SAC	-0.169	**0.838**	0.001	0.235	0.027	0.008	0.127	0.838	0.717	1.712
SOB	0.473	0.023	**0.909**	0.038	0.140	0.335	0.051	0.909	0.864	1.822
SOC	-0.004	0.485	0.194	**0.898**	0.001	0.000	0.050	0.898	0.777	1.471
TRU	0.660	-0.165	0.374	-0.026	**0.931**	0.142	0.062	0.931	0.907	2.059
UTB	0.522	-0.088	0.579	-0.017	0.377	**0.891**	0.097	0.891	0.818	2.315
UTC	-0.355	0.356	-0.226	0.223	-0.249	-0.312	**0.700**	0.700	0.588	1.417

Note: AVEs on diagonal; correlations below diagonal ; squared correlations above diagonal

Discriminant validity is established by ensuring that the squared correlation of each construct with every other construct is less than the AVE (Fornell & Larcker, 1981). Every measure passed this criterion. Therefore, we conclude that the remaining items (after removing PCPI1, UTC3, SOC2, and SAC1) demonstrate sufficient discriminant validity.

Construct Correlation Matrix

Tables B.3.1 and B.3.2 summarize the correlations among all first-order latent, reflective constructs for both the privacy calculus and relational commitment models.

Table B.3.1 Correlation Matrix – all Variables (Second-order constructs used where available)						
	Age	Benefits	Control settings	Costs	Disclosure	Gender
Age	1					
Benefits	0.042	1				
Control settings	-0.020	0.002	1			
Costs	-0.033	-0.19	-0.009	1		
Disclosure	0.010	0.208	-0.234	-0.084	1	
Gender	0.136	-0.026	0.038	-0.008	-0.059	1
Privacy concern	-0.125	0.021	-0.016	0.285	-0.09	-0.080
Relationship commitment	0.025	0.522	-0.004	-0.280	0.313	-0.057
Trust	0.041	0.455	0.059	-0.191	0.137	-0.062
Education	-0.288	-0.001	-0.018	-0.041	0.089	-0.066
Ethnicity	-0.041	-0.018	-0.001	0.008	-0.012	0.058

Table B.3.2 Correlation Matrix – all Variables (Second-order constructs used where available)					
	Privacy concern	Relationship Commitment	Trust	Education	Ethnicity
Privacy concern	1				
Relationship commitment	-0.148	1			
Trust	-0.175	0.490	1		
Education	0.055	0.000	-0.041	1	
Ethnicity	-0.025	-0.017	0.003	-0.051	1

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Examining the Overall Presence of Motorsports in the Southern United States

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Abstract

While American stock car racing may have grown out of the mill towns and moonshiners of the 1930's and 1940's, it has become a nationwide phenomenon with national and regional racing series conducting races in all geographic regions of the United States. Today, over half of NASCAR's national and regional races are held in the southern United States. Motorsports and motorsports-related tourism remain very prevalent in southern culture. This paper presents a model to capture the overall presence (and impact) of motorsports in the southern United States.

Introduction

Stock car racing in the United States started in the 1930's and 1940's in the mill towns of the American South where young men were faced with few choices, and limited excitement, other than their involvement with moonshining. The moonshine buyer would not come to their suppliers. So, the suppliers had to deliver the goods to their customers. To do so, and to avoid law enforcement, the moonshiners added extra power, suspension support, and handling to their cars. It is no wonder that these young men started racing these cars against one other. Eventually, local entrepreneurs would bulldoze the red clay of the Carolina Piedmont to create dirt tracks to host races. The growing sport of stock car racing became more formalized and offered entertainment and a form of escape for these working-class communities (Pierce, 2001; Klein, 2023).

During the early years of racing, many drivers complained that track owners or race promoters were not concerned about their safety and welfare. As a result, winning purses were not always paid, track maintenance did not always occur, and driver safety concerns were dismissed. In 1947, in a bar located above a local hotel, Daytona Beach garage owner and race promoter Bill France convened a group of car owners/drivers, race promoters, and auto manufacturer reps to try to create some formal structure to stock car racing. The result was the creation of the National Association for Stock Car Racing (NASCAR) with the first race run on the beaches of Daytona Beach, FL in 1948 (Pierce, 2001; Davis, 2009).

Many of today's mainstay tracks of NASCAR were built in the American South in those first 15 years, including (The Daily Downforce, 2023):

- North Wilkesboro (NC) Speedway in 1947
- Martinsville (VA) Speedway in 1947
- Darlington (SC) Raceway in 1950
- Daytona (FL) International Speedway in 1959
- Charlotte (NC) Motor Speedway in 1960
- Atlanta (GA) Motor Speedway in 1960
- Bristol (TN) Motor Speedway in 1961

Furthermore, many early drivers and champions such as Richard Petty, David Pearson, and Bobby Allison hailed from southern states. Monte Dutton covered NASCAR for the *Gaston (NC) Gazette* for over 30 years. He noted, "part of the reason that southerners identify with stock car racing is that it's southern. The South is the first place where (stock car racing) became a spectacle" (Davis, 2009). Still today, studies indicate that nearly 41 percent of NASCAR fans in the United States reside in the American South (American Media Group, 2023; Spire Motorsports, 2024; Yen, 2020).

While NASCAR started in the American South, the organization currently sanctions races and tracks all across the United States, Canada, Mexico, and other countries (see NASCAR, 2024d). Still, there remains a concentration of motorsports racing and tourism attractions across the southern United States. The purpose of this manuscript is to examine the broad impact and enduring presence that motorsports has across the southern United States. First, the foundational concepts of (a) Consumer Experience Tourism and (b) the Diffusion of Innovations are discussed. Second, a model to depict the many and varied components of motorsports events and motorsports tourism in the American South is presented. Third, each component of this model is discussed in further detail. Finally, some concluding remarks are offered.

Foundational Concepts Underlying Model Development

Consumer Experience Tourism in Motorsports

Darlington Raceway in Darlington, SC was the first superspeedway to host a NASCAR race back in 1950. A year earlier, a local businessman named Harold Brasington, who had attended the Indianapolis 500 a few years before that, sought to turn a cotton field into a paved superspeedway. Rather than build an oval-shaped track, the track was designed as an egg-shape to preserve a small pond on the property (Davis, 2009).

Darlington Raceway currently hosts two weekends of NASCAR auto racing each year, including a May weekend and Labor Day weekend. The 2024 Labor Day weekend (Thursday to Monday) will offer race fans the following events (Darlington Raceway, 2024a):

- Track Laps for Charity – opportunity to drive your personal vehicle around the track.
- Terrence F. Carraway Memorial 5K Run – opportunity to walk/jog around the track
- Two Races - NASCAR Cup Series and NASCAR Xfinity Series.
- NASCAR Driving School – drive a NASCAR race car in a timed session with a spotter providing driver assistance over the radio.
- Darlington Raceway Stock Car Museum – opportunity to learn more about the history of stock car racing, including the National Motorsports Press Association (NMPA) Hall of Fame.
- GEICO Infield Camping – opportunity to park a camper or RV in the in-field a watch race weekend events from this unique vantage point.

Race weekends at Darlington Raceway (or, really, any NASCAR track) provide an excellent illustration of Consumer Experience Tourism (CET) in action. Traditionally, 'Consumer Experience Tourism' involves the development of manufacturing plant tours, company museums, and company visitor centers to establish a bond between a consumer and brand as the consumer learns about the brand, its operation, production process, history, and historical significance (see Mitchell and Orwig, 2002). Here, the race track serves as the plant (e.g., where the race is held) and becomes a visitor center serving fans, including attending the museum and the chance to actually drive the track (Mitchell, Montgomery, and Mitchell, 2004).

Unlike other sports, fans to a NASCAR race can buy packages that allow them to (a): camp alongside the track in the infield; (b) access the race track and driver garages prior to the race; and (c) listen to sensitive team communications by renting scanners to follow their favorite drivers (Darlington Raceway, 2024b). No other sport provides fans such an immersive fan experience. NASCAR fans are notoriously brand loyal and are mindful that teams cannot race without sponsorship and will support sponsors with their purchases to demonstrate their appreciation (Stamey, 2022).

The Diffusion of Innovations and New Product Success Factors

Diffusion of Innovation (DOI) Theory, developed by Everett Rogers in 1962, is one of the most well-known and established theories in social science. A fifth and final edition of his ground-breaking research was published in 2003. Rogers (2003) described five categories of adopters in two main groups: earlier adopters and later adopters. Earlier adopters consist of innovators, early adopters, and early majority, while late majority and laggards comprise later adopters. Rogers identifies the differences between these two groups in terms of socioeconomic status, personality variables, and communication behaviors.

According to Rogers (2003), there are five main factors that influence the adoption of an innovation through a group:

1. *Compatibility* is the degree to which an innovation is perceived as being consistent with existing values, past experiences, and consumer needs.
2. *Trialability* is the degree to which an innovation may be experimented with on a limited basis.
3. *Relative Advantage* is the degree to which an innovation supersedes the idea before it.
4. *Observability* is the degree to which the results of an innovation are visible to others.
5. *Complexity* is the degree to which an innovation is perceived as difficult to understand and use.

NASCAR has been organizing and hosting multiple racing series now for over 50 years. Over this time, three or four generations of fans have been brought to the sport. This can be seen at any NASCAR race where grandparents, parents, and children all loudly support their favorite drivers. It is suggested here that (a) the sport of racing itself, and (b) NASCAR's willingness to provide an immersive fan experience, have both contributed greatly to this diffusion of fandom of motorsports racing through multiple generations. These critical success factors are discussed in the sections that follow.

Compatibility. As Henry Ford once said, "Auto racing started 5 minutes after the second car was built" (Jones, 2009). The southern and southeastern United States has a rich history of racing, including the formal creation of NASCAR in 1947 and the running of the inaugural race on the beaches of Daytona Beach, Florida in 1948 (NASCAR, 2024c). Automobile travel and individual mobility are important components of the American culture. Most small communities in the American South lack a developed mass transit system. So, people drive cars. Previously-noted auto writer Monte Dutton described the people's interest in auto facing as follows (Jones, 2009):

> *"Not everybody can hit a fastball, but everybody drives a car. They can't drive a car at 180 mph, but there is a certain way in which racing allows people to live vicariously to a greater extent than other sports."*

In the early days of NASCAR, founder Bill France was adamant that he wanted his drivers in American-made sedans so that working-class people would relate to this new sport (Davis, 2009).

Trialability. Motorsports fans can attend local and regional races close to home. With NASCAR's three national racing series, ticket prices for the Xfinity Series and Craftsman Truck Series tend be less expensive than NASCAR Cup Series tickets. For example, tickets prices for the October 2024 NASCAR races at Talladega Superspeedway were $45 for grandstand seats for both the Xfinity and Craftsman Truck Series and $95 for the NASCAR Cup Series. In addition to group discounts, the track offers discounting programs for families and children, college students, first responders, teachers, military members, and scout troops (Talladega Superspeedway, 2024). All of these efforts help to remove the 'price objection' that races are too expensive for a new or casual fan to attend.

Relative Advantage. As previously noted, NASCAR provides a very immersive fan experience, particularly when compared to other professional and team sports. Let's compare the NASCAR fan experience to the National Football League (NFL) fan experience.

Fan Element	NASCAR	National Football League
Ability to set up a camper or RV within the competition space	Yes	No
Ability to listen to team communication during the competition	Yes	No
Ability to walk the pits or sidelines before the competition	Yes	No
Ability to access the competition space (and run or drive your car)	Yes	No
Ability to play-along or ride-along while a professional to provide a full-speed competition experience	Yes	No

Extending this example further, fans do not get to take batting-practice from their favorite major league pitcher. They do not get to catch passes from their favorite quarterback. They do not get to attempt 40-yard field goals in their favorite stadiums. They do, however get to drive along and ride-along with trained drivers on NASCAR tracks.

Observability. Auto racing is a multi-sensory fan experience that combines sight, sound, and touch as fans can feel the breeze created by a pack of fast-moving racing cars speeding by at 180 miles per hour. In-car cameras and microphones bring the racing experience from the track to the couch, recliner, or bar stool. Additionally, high resolution video games have allowed fans to virtually drive their favorite tracks and experience both thrills and challenges of high-level motorsports.

Current NASCAR driver (and 2024 Daytona 500 Champion) William Byron credited his early career in online racing as a key contributor to his on-track success (De la Fuente, Ramsay, and Davies, 2024). Unlike drivers before him who rose from the small local dirt tracks to drive in NASCAR's highest series, Bryon got his start in racing in iRacing, the racing simulator popular among today's younger drivers (McFadin, 2017). Similarly, Sony Pictures released a 2023 film, *Gran Turismo*, that tells the true story of Jann Mardenborough and his unlikely rise from video-gamer to race car driver. Mardenborough beat out over 90,000 video gamers to earn a spot in a driver development program sponsored by Nissan and Sony Computer Entertainment (Piccotti, 2023).

Complexity. At its core, the goal of motorsport racing is somewhat simple: drive your car faster than others over a period of time, including the time needed to service the car. Granted, modern-day race cars possess advanced technologies that are supported by telecommunications and computerized systems. The ideal path around a race track can be modeled on computer simulators. Data analytics aids in decision-making. Still, the goal is very simple: go fast and beat the others to the finish line. As fictional race driver Ricky Bobby said in the 2006 film *Talladega Nights*, “if you ain’t first, you’re last.”

A Model to Capture the Overall Presence of Motorsports in the Southern United States

Up until this point, the discussion has been largely about NASCAR. In the sections that follow, NASCAR’s presence in the southern United States will be further examined. Additionally, other forms of auto racing and broad-based motorsports-tourism, as well as driver education and motorsports-related academic programs, must be added to the discussion to truly capture the totality of the presence of motorsports in the southern United States. Figure 1 (purposefully presented in the image of a racing tire) is advanced to capture the overall presence of Motorsports in Southern United States.

Figure 1: Motorsports-Related Activities in the Southern USA

Source: Original.

For this study, the Mason-Dixon line (border of Pennsylvania, Maryland, and Delaware) is used as the demarcation line between northern and southern states. The region is extended west as far as Texas and north to include Oklahoma, Arkansas, Tennessee, Kentucky, and West Virginia (See Britannica, 2024). The state of Arizona, a host site for racing series, is considered is considered the southwestern United States.

NASCAR National Racing Series – 2024 Season

There are three sanctioned NASCAR national racing series: (1) NASCAR Cup Series; NASCAR Xfinity Series; and (3) Craftsman Truck Series (NASCAR, 2024a). In total, 31 race tracks are used. As illustrated in Table 1, 14 of these 31 race tracks (45 percent) are located in the American South. Some race tracks, like Darlington noted above, host two races per year. In fact, 7 of 10 tracks (70 percent) that host two NASCAR Cup Races are located in the southern United States. Overall, NASCAR conducted over half of its races in each of its national race series in the southern and southeastern United States in during the 2024 season. This information is presented visually in Figure 2.

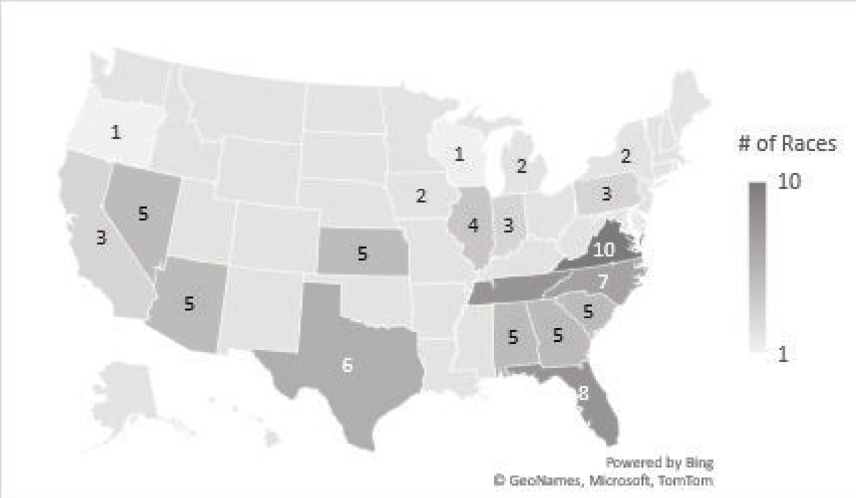
Table 1: Tracks Hosting NASCAR's National Racing Series

Southern Tracks			
Track	NASCAR Cup	NASCAR Xfinity	Craftsman Truck
Atlanta Motor Speedway (GA)	2 Races	2 Races	1 Race
Bristol Motor Speedway (TN)	2 Races	1 Race	2 Races
Charlotte Motor Speedway (NC)	1 Race	1 Race	1 Race
Charlotte Motor Speedway Road Course (NC)	1 Race	1 Race	
Circuit of the Americas (COTA) in Austin (TX)	1 Race	1 Race	1 Race
Darlington Raceway (SC)	2 Races	2 Races	1 Race
Daytona International Speedway (FL)	2 Races	2 Races	1 Race
Homestead-Miami Speedway (FL)	1 Race	1 Race	1 Race
Martinsville Raceway (VA)	2 Races	2 Races	2 Races
Nashville Superspeedway (TN)	1 Race	1 Race	1 Race
North Wilkesboro Speedway (NC)	1 Race		1 Race
Richmond Raceway (VA)	2 Races	1 Race	1 Race
Talladega Superspeedway (AL)	2 Races	2 Races	1 Race
Texas Motor Speedway (TX)	1 Race	1 Race	1 Race
Sub-Totals	21	18	15

Non-Southern Tracks			
Track	NASCAR Cup	NASCAR Xfinity	Craftsman Truck
Chicago Street Race (IL)	1 Race	1 Race	
Dover Motor Speedway (DE)	1 Race	1 Race	
Indianapolis Motor Speedway (IN)	1 Race	1 Race	
Iowa Speedway (IA)	1 Race	1 Race	
Kansas Speedway (KS)	2 Races	1 Race	2 Races
Las Vegas Motor Speedway (NV)	2 Races	2 Races	1 Race
Los Angeles Memorial Coliseum (CA)	1 Race		
Lucas Oil Indianapolis Raceway Park			1 Race
Michigan International Speedway (MI)	1 Race	1 Race	
Milwaukee Mile (WI)			1 Race
New Hampshire Motor Speedway (NH)	1 Race	1 Race	
Phoenix Raceway (AZ)	2 Races	2 Races	1 Race
Pocono Raceway (PA)	1 Race		1 Race
Portland International Raceway (OR)		1 Race	
Sonoma Raceway (CA)	1 Race	1 Race	
Watkins Glen International (NY)	1 Race	1 Race	
World Wide Technology Raceway (IL)	1 Race		1 Race
Sub-Totals	17	14	8
Southern U.S. Events	21 (55%)	18 (56%)	15 (65%)
Total Events	38 (100%)	32 (100%)	23 (100%)

Source: Original table from NASCAR schedules on website.

Figure 2: NASCAR National Series Races Hosted by State



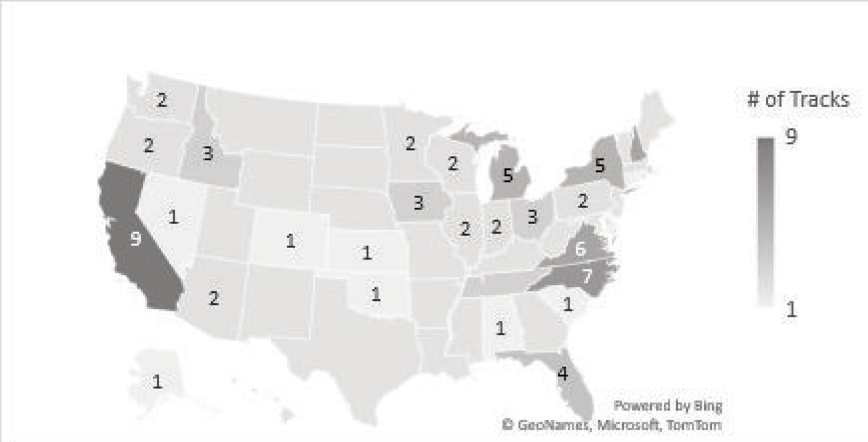
Source: Original.

NASCAR Regional Racing Series – 2024 Season

NASCAR sanctions three regional racing series with races run across the United States (29 states) and Canada (4 provinces): (1) NASCAR Advance Auto Parts Weekly Series (47 tracks); (2) ARCA Menards Series (30 tracks); and (3) NASCAR Whelen Modified Tour (11 tracks). In total, 88 local race tracks are involved. These regional tracks are presented visually using the heat-mapping feature in Excel. This heat-map (Figure 3) shows the geographic distribution of these regional tracks in the United States. Given the geographic focus on this manuscript, the Canadian tracks (7 in all) were <u>not</u> included and mapped in Figure 3.

As previously noted, NASCAR's national series run over half of their races in the southern United States. By comparison, the races in NASCAR's regional racing series are more widely-distributed across the United States and Canada. For example, California (n=9), New Hampshire (n=6), New York (n=5), and Michigan (n=5) are the larger host states outside of the southern United States. It must be noted that North Carolina (n=7) and Virginia (n=6) were ranked 2nd and 3rd-tie behind California.

Figure 3: NASCAR Regional Race Host Tracks by State



Source: Original.

Road Racing / Rallies

In addition to oval race tracks (and oval tracks that convert to road courses such Daytona International Speedway and Charlotte Motor Speedway), there are many road courses spread across the southern United States. These facilities host IndyCars, Trans Am Series, IMSA Weathertech Sportscars, and other racing leagues. Some examples are listed below:

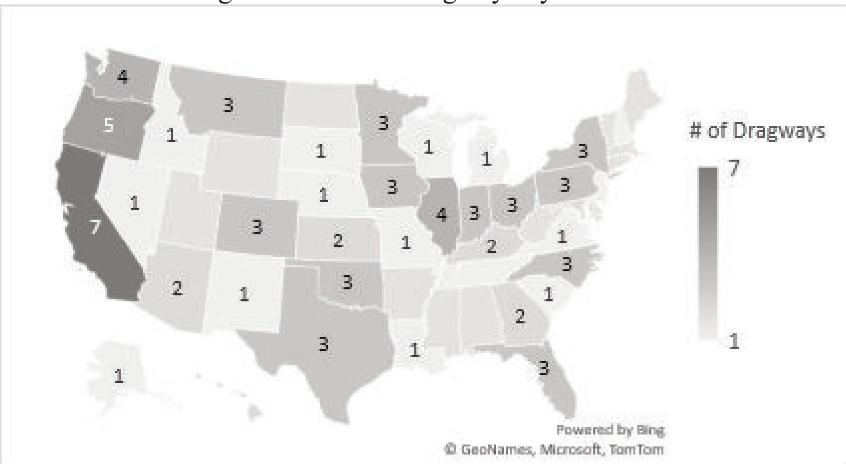
- Sebring International Raceway (Sebring, FL)
- Road Atlanta (Braselton, GA)
- NOLA Motorsports Park (Avondale, LA)
- Virginia International Raceway (Alton, VA)
- Barber Motorsports Park (Birmingham, AL)
- Carolina Motorsports Park (Kershaw, SC)
- Summit Point Motorsports Park (Summit Point, WV)

These same tracks often host motorcycle racing as well. The reader should note the Circuit of the Americas (COTA) in Austin, TX is a stop of the NASCAR national series.

Drag Racing

The National Hot Rod Association (NHRA) is the governing body for drag racing in the United States and Canada. NHRA-sanctioned dragways (which tend to be ¼ mile tracks) can be found in the following southern states: Florida, Georgia, Kentucky, Louisiana; Maryland; North Carolina; South Carolina; Tennessee; Texas; and Virginia (NHRA, 2024). Figure 4 shows the visual distribution of these dragways in the United States. Given the geographic focus on this manuscript, the Canadian dragways (9 in all) were not included in Figure 4.

Figure 4: NHRA Dragways by State



Source: Original.

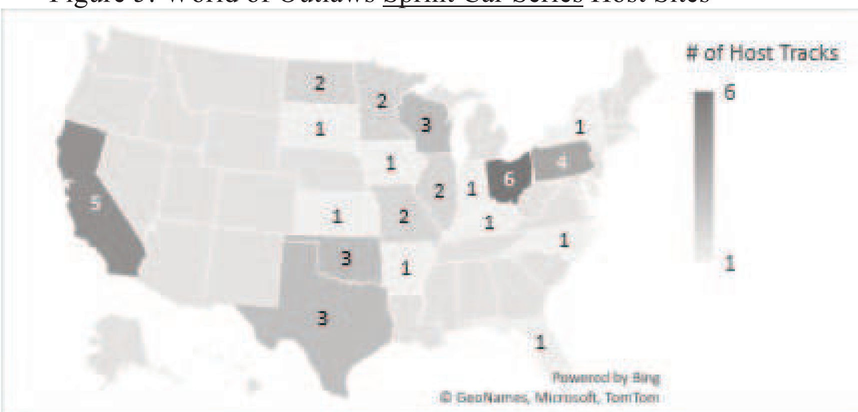
F1 / IndyCar Racing

Formula 1 is an open-wheel international racing series that runs a 24-race schedule (known as Grand Prix's) across 5 continents. In 2024, Formula 1 will conduct three races in the United States (Miami, FL; Austin, TX; and Las Vegas, NV) (Formula 1, 2024). The Circuit of the Americas (Austin, TX) currently hosts the Formula One United States Grand Prix (Circuit of the Americas, 2024) while the circuits (or race tracks) in Miami and Las Vegas are temporary tracks using existing streets with modifications. Fans of open-wheeled racing in the southern United States can also watch the IndyCar series compete in three location during the 2024 season: St. Petersburg, FL; Birmingham, AL; and Nashville/Lebanon, TN (IndyCar, 2024).

World of Outlaws

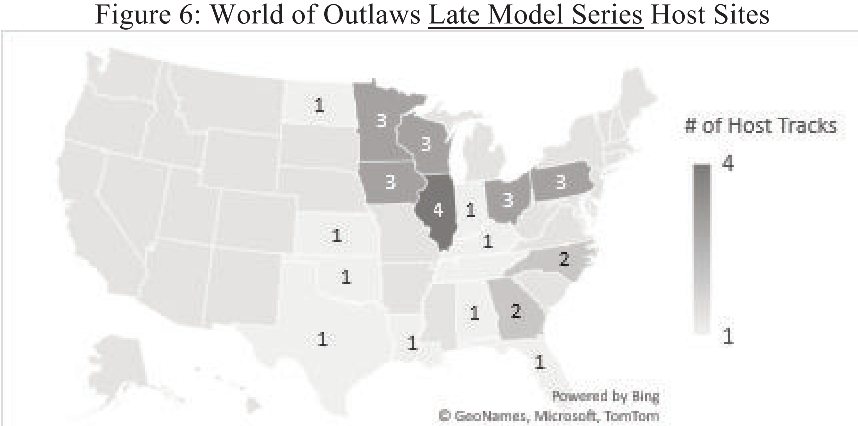
The World of Outlaws (with its headquarters in Concord, NC, very near to most NASCAR team garages) operates touring dirt-track racing series for both Sprint Cars and Late Model Series cars. Races are contested on local dirt tracks across the United States with most race weekends consisting of a series of races over 3-4 consecutive days. Both series culminate their seasons with a final week of racing at The Dirt Track of Charlotte in Concord, North Carolina (World of Outlaws, 2024). Periodically, a fan's favorite NASCAR driver may compete in World of Outlaw races during the mid-week. The locations that hosted the World of Outlaws series in 2024 are presented visually using the heat-mapping feature in Excel to create Figure 5 and Figure 6. The reader can see these two series have less of a presence in the southern United States compared to the remainder of the country. Still, they conduct their championship in the American South (very near to their headquarters location).

Figure 5: World of Outlaws Sprint Car Series Host Sites



Source: Original.

Figure 6: World of Outlaws Late Model Series Host Sites



Source: Original.

Local Tracks

There are currently an estimated 900 short (racing) tracks operating in the United States. These tracks tend to be less than a mile in length and may have a dirt or paved asphalt racing surface. The local tracks, which can be found in all 50 states, provide thousands of racers a chance to compete in motorsports racing at the grassroots level (Neveu, 2021). Some racers, as young as seven years old, can begin racing in go-karts in races sanctioned at local tracks by the United States Pro Kart Series (2024). Race track host communities realize many benefits from their local tracks, including: the economic impact of racing; youth and community development; support of local charitable initiatives; and preservation of local culture, heritage, and identities (Thunderbird Speedway, 2024).

Throughout history, some of these local tracks have ceased operations for a variety of reasons, including competitive pressures from neighboring tracks or the sale of the racetrack property for redevelopment. For example, Myrtle Beach Speedway ceased operations in 2020 after 62 years of racing. The property was sold to developers who intended to convert the land, which is located along a main traffic artery to the popular beach community, for use in housing and commercial retail development (Shoemaker and Blondin, 2022). At the national level, only two of NASCAR's original tracks (Martinsville, VA and North Wilkesboro, NC) that hosted races in the inaugural 1949 "strictly stock car" season remain in operation today (ESPN, 2024).

Driving Experiences

At 17 NASCAR tracks (such as the Darlington Raceway example presented in the Introduction) fans can drive a NASCAR race car around the track with no pace car and no instructor accompanying them. Or, fans can choose to ride-along with a certified NASCAR driver (NASCAR Driving Experience, 2024). Half of the tracks offering such a fan experience are located in the southern United States, including:

- Atlanta Motor Speedway
- Charlotte Motor Speedway
- Darlington Raceway
- Daytona International Speedway
- Homestead-Miami Speedway
- Nashville Superspeedway
- Richmond Raceway

- Talladega Superspeedway
- Texas Motor Speedway

There are also driving schools offered by former drivers, such as The Racing Experience, that are offered periodically at 55 race tracks across the United States, including a concentration of race tracks in the southern United States (The Racing Experience, 2024). Finally, BMW owners can travel to the BMW Performance Center in Greer, SC to learn how to get the best performance from our personal automobiles at the facility adjacent to the manufacturing facility in Upstate South Carolina. The BMW Performance Center (2024) describes the experience as follows:

> *"Discover why the Ultimate Driving Machine isn't just a tagline. Each BMW was built for maximum enjoyment at the limit, and you'll be able to experience every spine-tingling sensation behind the wheel of our high-performance driving classes."*

Motorsports-Related Tourism

Fans of motorsports have many other ways to interact with their sport and favorite drivers that are found all around the southern United States. Some examples are provided below.

Track Tours and Visitor Centers. Many NASCAR tracks provide guided tours for visitors and often include at least one lap around the track in a bus, tram, or other vehicle. For example, visitors to the Daytona International Speedway can choose between a 60-minute Speedway tour or a more immersive 2.5-hour VIP tour. Daytona Speedway also houses the Motorsports Hall of Fame of America that honors success in all forms of racing and motorsports: stock cars; sports cars; open-wheel; motorcycles; drag racing; land speed records; powerboating; and aviation (Daytona International Speedway, 2024). Similar track tours are offered by Charlotte Motor Speedway, Atlanta Motor Speedway, Bristol Motor Speedway, Talladega Superspeedway, and many others.

Team Garages and Driver Museums. Approximately 90 percent of NASCAR team garages are located in Concord, Kannapolis and the surrounding communities in North Carolina. The area lies northeast (and adjacent to) the city of Charlotte and includes Charlotte Motor Speedway, zMAX Dragway, and the Dirt Track of Charlotte. Most race teams welcome visitors for a behind-the-scenes look at race car preparation and offer viewing areas, museums, or team stores. (Explore Cabarrus, 2024; Project543, 2024).

Fans can also visit many stand-alone museums created by retired drivers, team owners, and motorsports enthusiasts. For example, the Memory Lane Historical Motorsports and Automotive History Museum in Mooresville, NC includes over 100 vehicles and exhibits. As noted on their website, “it’s a classic car museum, NASCAR museum, muscle car museum, movie museum, toy museum, and history museum all in one!” (Memory Lane, 2024).

NASCAR Hall of Fame driver Richard Petty and his family invite motorsports fans to visit their museum located on the property where the Petty race shop was based for decades in Randleman, NC (just south of Greensboro, NC). The race shop has since moved to Concord, NC (like most race teams). On their website, Richard Petty offers the following personal invitation to race fans (Petty Museum, 2024):

> *“Since we first opened our doors in 1988 we have welcomed thousands of race fans from all around the world. We are so proud of our family's rich history in NASCAR. If you come here, you see the history of NASCAR. We ran in the very first race and we’ve been running them ever since.”*
>
> *“Most museums, they’ll take the stuff from the original place and put it in a place where it loses its authenticity. When you walk in here, you’re in the middle of the history. Not only the museum but you’re walking on historic ground that’s had race cars. Two hundred and sixty-eight race cars win races out of this one shop to be exact.”*

Wood Brothers Racing, founded in 1950, operates the longest continuously-operated NASCAR Cup team. Like the Petty family, their museum (located in Stuart, VA) provides visitors with a living history of motorsports (Wood Brothers Racing Museum, 2024). In all, both Wood Brothers (Glen and Leonard) as well as 10 of their former drivers have all been inducted into the NASCAR Hall of Fame (NASCAR Hall of Fame, 2024).

Halls of Fame. The NASCAR Hall of Fame opened in Uptown Charlotte in 2010. Here, visitors can learn the history and heritage of NASCAR. The goal of the NASCAR Hall of Fame is to “honor NASCAR icons and create an enduring tribute to the drivers, crew members, team owners and others that have impacted the sport in the past, present and future.” (NASCAR Hall of Fame, 2024a).

Additionally, many states with a concentration of motorsports facilities or teams have created state Hall of Fame museums. Some of the larger museums include: Georgia Racing Hall of Fame (Dawsonville, GA); North Carolina Auto Racing Hall of Fame (Mooresville, NC); and the International Motorsports Hall of Fame and Museum (Talladega, AL). Fans of drag racing can visit the International Drag Racing Hall of Fame, which is part of the Don Garlits Museum of Drag Racing in Gainesville, Florida. Don Garlits is a Hall of Fame drag racer (Garlits.com, 2024).

Motorsports-Related Academic Programs

A 2021 study, commissioned by the International Automobile Federation (FIA), reported the motorsport industry contributed over $188 billion to the global economy. The study also revealed that the motorsport industry supports 1.5 million paid jobs (Yeomans, 2021). Many schools in the Southern United States have developed motorsports-related academic programs to serve students interested in related careers. These programs, ranging from high school to graduate school, are listed in Table 2.

Table 2: Motorsports-Related Educational Programs

K-12 Programs	Associate Degree Programs	Bachelor's Degree Programs	Graduate Programs
• Conway, SC – The Palmetto Academy for Learning Motorsports (PALM), only motorsports high school in the country.	• Forsyth Technical Community College (Winston-Salem, NC) – AAS in Race Car Technology • Rowan-Cabarrus Community College (Salisbury, NC) – AAS in Motorsports • Lanier Technical College (Oakwood, GA) – AAS in Motorsports Vehicle Technology • Patrick Henry Community College (Martinsville, VA) – AAS in Motorsports Technology • South Georgia Technical College (Americus, GA) – AAS in Motorsports Vehicle Technology	• Belmont Abbey College (Belmont, NC) – B.A. in Motorsports Management • University of North Carolina Charlotte (UNCC) – B.S. in Motorsports Engineering • Clemson University (Clemson, SC) – B.S. in Automotive Engineering • Winston-Salem State University (NC) -B.S. in Motorsports Management	• Belmont Abbey College (Belmont, NC) – M.A. in Motorsports Management • Belmont Abbey College (Belmont, NC) – MBA with Concentration in Motorsports Management • Clemson University (Clemson, SC) – M.S. in Automotive Engineering • Clemson University (Clemson, SC) – Ph.D. in Automotive Engineering

Source: Original from academic program websites/catalogs.

It should be noted that, at the time of this writing, current NASCAR Craftsman Truck Series driver Rajah Caruth is currently enrolled in the B.S. in Motorsports Management program at Winston-Salem State University (NC) while concurrently pursuing his career as a driver.

Miscellaneous

As previously noted, Henry Ford once noted the propensity of drivers to want to race and compete. Not all racing in the American South takes place outdoors on dirt or oval tracks. Below are a few examples.

Indoor Kart Racing. The family of Hall of Fame driver Mario Andretti, including his sons who themselves are former drivers, have opened a series of Andretti Indoor Karting and Games Centers. Racing fans can drive electric go-karts on an indoor track while racing others (Andretti, 2024). Of the nine locations currently available, 8 of the 9 locations can be found in the southern United States:

1. Orlando, FL
2. Marietta, GA
3. Buford, GA
4. Katy, TX
5. The Colony, TX
6. Grand Prairie, TX
7. Fort Worth, TX
8. San Antonio, TX

As the name implies, the Andretti Centers combine go-kart racing, arcade games, and virtual reality games along with food and beverage services.

Mud Bogging. Mud bogging is an off-road motorsport that requires you to drive through a pit filled with mud. Typically, two vehicles are paired for competition with the goal being to: (a) travel further through the mud than your competition; or (b) cross the mud pit faster than your competition. Mud bogging is popular across the United States and Canada with some of the more popular (i.e., larger) events found in the southern United States (Unrau, 2024). The 2024 Extreme Mudding Tour will host competitions in the following southern States: Alabama; Florida; Georgia; Kentucky; North Carolina; Oklahoma; South Carolina; Texas; and Virginia. The Iron Horse Mud Ranch (Perry, Florida) claims of offer mudders "the best mud holes and trails in the country." Below is a description of their facility (Iron Horse Mud Ranch, 2024):

> *"The best mud park in Florida is bigger and better than ever! IHMR is 520 acres of prime swamp land turned into what we now call "IRON HORSE MUD RANCH." Our Ranch offers you some of the best mild to wild trails and bogs in the country. So bring on your ATV's, UTV'S, 4X4'S, SUV'S, RV'S, campers, tents and Mud Trucks for the adventure of a lifetime."*

Powerboat Racing. Powerboat races can be divided into two groups: (1) Offshore Powerboat Races – courses constructed on the ocean; and (2) Inshore Powerboat Races – courses constructed on sheltered or inland waterways such as sheltered bays, lakes and rivers (Top End Sports, 2024). The American Power Boat Racing Association (APBA) sanctions over 150 races per year, including the following example races in the southern United States in 2024:

- Guntersville Lake HydroFest – Lake Guntersville (Alabama)
- 2024 Speed Freek RC Offshore Challenge – Lake Eustis (Florida)
- New Martinsville Vintage Regatta – Ohio River (West Virginia)
- Thunder on the Choptank – Choptank River (Maryland)
- 40th Sarasota Powerboat Grand Prix – Gulf of Mexico (Florida, Offshore)
- Orange Cup Regatta – Lake Hollingsworth (Florida)
- Tabor City – Halloween Regatta – Lake Tabor (North Carolina)
- Key West World Championships – Key West Harbor (Florida, Offshore)

Concluding Remarks

The southern United States has a rich history of racing, including the formal creation of NASCAR in 1947 and its inaugural races on the beaches of Daytona, Florida in 1948 (NASCAR, 2024c). Iconic tracks located in North Wilkesboro, Martinsville, Darlington, Daytona, Charlotte, Atlanta, and Bristol were built during NASCAR's first 15 years and became pilgrimages for the growing number of NASCAR fans (Davis, 2009). Today, each of NASCAR's three national series run over half of their races in the southern United States. These races bring much economic activity to the host communities. For example, Darlington Raceway has an economic impact of $110 million annually. Track President Josh Harris acknowledged this importance in a 2024 interview (Benson, 2024):

> *"Darlington Raceway is proud to be a major part of South Carolina's sports tourism legacy, and we're also proud to be a key driver of the future. Today, NASCAR fans from all around the world make the Palmetto State a can't-miss destination twice a year."*

NASCAR's regional tracks (which host the developmental series) can be found in the region, particularly in Virginia, North Carolina, and Florida. However, these regional track events are more dispersed across more U.S. states than the national racing series events. Additional forms of racing, such as Formula 1, Road and Rally Races, Drag Races, Outlaw Races, and others can be found all over the region as well as mud bogging, powerboats, and motorcycling.

The region is rich in motorsports-related tourism attractions, such as museums, halls of fame, track tours, driving schools and experiences, and many others. These consumer experience tourism sites help to strengthen the bond between racing fans, their favorite sport, and their favorite teams. Academic programs have been developed to provide an educational pathway to careers in motorsports. In this manuscript, the authors attempted to illustrate the overall presence of motorsports in the southern United States and, concurrently, to demonstrate its importance to the local culture. Each generation of motorsports racing fans helps to strengthen these bonds. It is anticipated that motorsports and motorsports-tourism will continue to flourish in the Southern United States in the years ahead.

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Testing for Exchange Rate Bubbles using the Recursive Flexible Window Methodology: Case Study: US Dollar / Canadian Dollar

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Abstract

Identifying and dating financial bubbles in real time is in the forefront of current empirical research. Their nonlinear structure makes the econometric testing extremely challenging. The seminal contribution in statistical testing of this type of data, is Phillips, Shi, and Yu (2015). It gives consistent results and delivers significant power gains even when multiple bubbles occur. As a first step, here, we apply it to the US dollar / Canadian dollar, over a long run period.

1. Introduction

History is replete with incidents of financial crises, which ex-post become a wakeup call for policy makers and the public. Experts have said that the 2008-09 crisis was preceded by "asset market bubbles" and / or "excessive credit expansion." It is true that we do not have good quantitative criteria which can ex-ante indicate the beginning of a "bubble" being built in the asset / credit markets which may lead to a crisis in the future. Thus, the task at hand is to try to determine possible quantitative measures that a speculative bubble is probably taking shape. In the economics literature we have multiple tests to detect the crisis "ex-post," and then explain it. But there are no tests to "ex-ante" identify the origination of a bubble which is in the making.

Phillips, Wu, and Yu (PWY henceforth, 2011) presented a recursive method to pinpoint excessive movements in asset prices through the early detection of bubbles. The next step in the evolution of this class of tests was to create the one that could decipher multiple bubbles in the same sample period. This is where the Phillips, Shi, and Yu (PSY henceforth, 2014) work is relevant. This paper offers a powerful and credible "quantitative metric" to detect exuberance in financial data, right where it is originating. PSY (2014) presents a recursive econometric technique to detect / test / date financial bubbles in the same sample data and separate them when multiple bubbles are present. Here the authors extend on their (PWY, 2011) methodology, which is based on a sequence of forward recursive right tailed ADF unit root tests, using the Sup ADF (designated SADF) measure. This process allows for a dating strategy to identify the origination and termination dates of a specific bubble. This is achieved by using "backward regression techniques."

But what if there are multiple bubbles, originating and decaying in sequence over time? PSY (2014) present an extension of the SADF tests, in form of a generalized SADF called the GSADF method. It includes a recursive backward regression technique, to time identify the origin and collapse of bubbles. This sequential test works in deciphering multiple bubbles from explosion to collapse and separate them over time. They apply it to the S&P 500 stock market data from January 1871- December 2010. It has been able to identify all the historically documented bubble episodes, like the 1929 crash, 1954 boom, 1987 black Monday and the latest dot-com bubble.

The idea is to identify bubbles in real time data and then look for the "markers" identifying those bubbles / episodes of market exuberance. The problem is that the standard ADF test can identify extreme observations but cannot differentiate a bubble phase observation from one which is part of a natural growth trajectory. Thus, ADF tests may result in "pseudo bubble detection." Making this distinction is the major contribution of this PSY (2014) test. The authors run backward sup ADF or backward SADF tests, to improve the chances of deciphering a bubble from a growth trajectory. The recursive test means running SADF backwards on the same sample.

In section 2, we present a literature review of this line of research. In section 3, we apply the PWY test, the sequential PWY test and the CUSUM test, and do an examination for the presence of multiple bubbles in the US Dollar-Canadian Dollar exchange rate, in a data set extending over six decades. This should be able to pinpoint all the bubbles since this is a long enough time period. Section 4 contains some concluding remarks.

2. Literature Review[1]

Bettendorf & Chen (2013) and Jiang et. al. (2015) empirically examine the explosive behavior of the Sterling-Dollar and Chinese RMB-Dollar exchange rates, respectively. Bettendorf & Chen (2013) use the GSADF test to examine the existence of bubbles in the Sterling-dollar exchange rate from January 1972 to June 2012 and they found evidence of explosive behavior in the nominal exchange rate. According to them, this finding of explosive behavior in the nominal exchange rate could not simply be interpreted as the evidence of rational bubbles. The explosiveness in the nominal exchange rate may be driven either by rational bubbles or explosive fundamentals themselves.

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[1] Our literature review owes a lot to "Are there bubbles in the exchange rates? Some evidence from G10 and emerging markets countries" by Hu and Oxley, 2016.

Similarly, Jiang et al. (2015) applied the same bubble-detection test to explore the presence of bubbles in Chinese RMB-dollar exchange rate between July 1995 and October 2013 and they found explosive behavior in the nominal exchange rate. This explosive behavior in the nominal exchange rate is explained by both rational bubbles and relative prices of traded goods.

A number of older studies have tested for bubbles in the exchange rates. Evans (1986) found evidence to support the presence of bubbles in the Sterling-dollar exchange rate between 1981 and 1984. Similarly, Meese (1986) provided evidence of bubbles for the dollar-deutsche mark and Sterling-dollar exchange rate using monthly data between 1973 and 1982. Wu (1995) applied the Kalman filter technique to estimate and test for exchange rate bubbles between the US dollar, the British pound, the Japanese Yen, and the Deutsche Mark (using monthly data over 1974-1988) but found no significant evidence of bubbles in these exchange rates. Van Norden (1996) investigated the existence of speculative bubbles in exchange rates of the Japanese yen, the German mark, and the Canadian dollar from 1977 to 1991 by applying a new regime switching test.

Diba & Grossman (1988) defined a rational bubble as a belief that an asset's price depends on a variable (variables) which is not relevant to fundamentals. They used data for Canadian dollar, the Danish krone, the Japanese yen, and the South African rand against the US dollar covering the period from January 1989 to December 2004. Three different bubble detection procedures have been used: the augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests, the Johansen's multivariate cointegration test and the duration dependence test of McQueen & Thorley (1994). All these tests provide firm evidence of no rational speculative bubbles in theses currency pairs.

The presence of bubbles displays a particular kind of regime-switching behavior by implying coefficient restrictions on a simple switching-regression model of exchange rate. Empirical results are sensitive to the choice of exchange rate fundamentals and measurement of exchange rate innovations. Elwood et al. (1999) made use of state-space models and Monte Carlo experiments to explore the presence of a stochastic rational bubble in the Japanese and German exchange rates over the period of December 1984 to November 1998. According to the theory of uncovered interest parity, a series under rational expectation is supposed to be white noise. They therefore inspected this condition for evidence of bubbles. A finding of a deviation from white noise implies the existence of a stochastic rational bubble. Their results suggest a bubble had burst between the end of March and the end of April of 1990, which coincided with economic turmoil in Japan and Germany.

3. Empirical Application and results:

In the Appendix, we describe the reduced form model, the new rolling window recursive test and its limit theory and elaborate on the data stamping strategies to identify and separate multiple bubbles in the same sample period, and discusses the size, power and performance of the dating strategy tests.

We use monthly data for the Canadian Dollar exchange rate (Canadian Dollar per U.S. dollar) for the period January 1957 to December 2018, for a total of 744 observations. This data set was obtained from the OECD database. We then conduct the SADF and the GSADF tests on the stock price index according to the basic model in eq.(1) in the Appendix. The results are given in table 1.

Table 1: Canadian Dollar per U.S. dollar

	Test Statistic	Finite Sample Critical Values		
Number of observations = 744		90%	95%	99%
SADF	1.8766	1.2237	1.4770	2.0017
GSADF	3.2273	2.0551	2.3202	2.8119

PSY 2015 state that the results of the tests may be sensitive to the choice of the window size. We use a rule recommended by them, as described in the appendix, to choose the appropriate window size for our data. Also given are the critical values of the two tests obtained from 2000 replications of the data in each case.

Both tests find evidence of bubbles or explosive sub-periods in the data for the Canadian Dollar exchange rate (test statistic in each case exceed the critical values for both test statistics considered). We then conduct a bubble monitoring exercise for the data using the backward ADF test and its critical value (using the PWY strategy), and the backward SADF statistic and its critical value (using the PSY strategy). This is done in figures 1 – 2.

Figure 1 FTSE 100 Backward ADF statistic

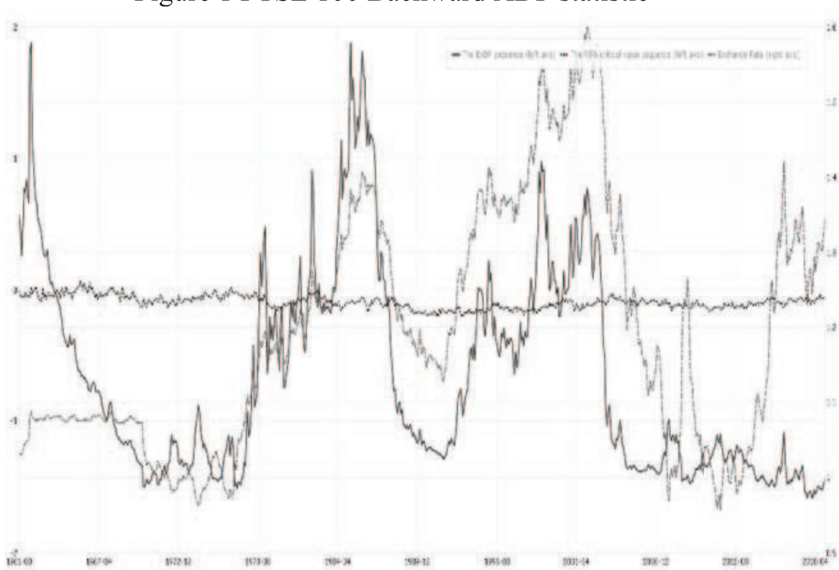

Figure 2 FTSE 100 Backward SADF statistic

In each of the above graphs the solid line that moves up and down represents the relevant test statistic, and the broken line which runs almost horizontally across the graph represents the critical value. We also include the exchange rate (the dashed line that fluctuates along with the test statistic, measured on the right axis) for reference. Figure 1 presents results from the use of the backward ADF test from the PWY paper, and Figure 2 presents results from the use of the backward SADF statistics from the PSY paper. In Figure 1 the existence of a bubble (test statistic greater than the critical value) is evident in the 1980s and again in the late 1990s and early 2000s, which corresponds with the technology bubble and its subsequent bursting. There is, however, no bubble around the financial crisis of 2008-09, in line with results that the authors have from the study of U.S. stock prices. Figure 2 shows evidence in favor of a bubble for the late 1990s to early 2000s (just like in figure 1), but also seems to show bubbles (short ones) in all decades of the data. The ability of the BADF statistic to detect multiple bubbles is suspect, and therefore the results in Figure 2 (based on the PSY paper) are more reliable.

4. Conclusion

The new test, the GSADF procedure is a recursive test, able to detect multiple bubbles. It is a rolling window, right sided ADF unit root test, with a double sup-window selection criterion. The SADF test is good, but it cannot credibly detect multiple bubbles over the same sample data set. The GSADF test overcomes this weakness and has significant discriminatory power in detecting multiple bubbles. We have evidence for the existence of bubbles in the1990s for the Canadian dollar exchange rate. There is some evidence for bubbles in the 2000s and later, including around the time of the financial crises of 2008. This may be due to either rational bubbles or explosive fundamentals, as found by a number of other studies. Since we are studying the Canadian dollar, existence of bubbles may also be explained by trade issues between the countries. It is also possible that a divergence between the relative prices of traded and non-traded goods could contribute to exchange rate bubbles. The sharp increase in real estate prices in the US prior to 2008 potentially leading to an overvaluation of the U.S. dollar vs the Canadian dollar and therefore leading to a bubble in the exchange rate. This would require further analysis in order to reach a definitive conclusion.

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Appendix:

Brief description of the Phillips, Shi, and Yu (2015) econometric procedure.

1. Rolling window test for bubbles
The standard asset pricing model is:

$$P_t = \sum_{i=0}^{\infty} (\frac{1}{1+r_f})i \; E_t(D_{t+i} + U_{t+i}) + \mathrm{B}_t \tag{1}$$

where
P_t = after dividend price of an asset
D_t = payoff (dividend) from the asset
r_f = risk free interest rate
U_t = unobservable fundamentals
B_t = bubble component

Here $P_t^f = P_t - B_t$ (market fundamentals) and B_t satisfies the sub martingale property

$$E_t = (B_{t+1}) = (1 + r_f)B_t \tag{2}$$

This equation sets up the alternative scenarios for the presence /absence of bubbles in the data. For example: If there are no bubbles, the B_t =0, then the degree of non-stationarity [I(0) or I(1)] of asset prices is controlled by asset payoffs or dividends (D_t) and the unobservable economic / market fundamentals. A possible outcome would be If D_t is an I(1) process, then U_t must be either I(0) or I(1) and asset prices can at the most be a I(1) process. But based on eq. (2), if there are bubbles, then asset prices will be explosive. Thus, when the fundamentals are I(1) and D_t is first difference stationary, we can infer bubbles if asset prices show evidence of explosive behavior. Eq (1) is one way to include a bubble variable in the standard asset pricing model. The advantage of the reduced form model is that it pretty much encompasses all standard formulations as intrinsic bubbles, herd behavior and time varying discounting processes.

Explosive behavior in asset prices is a primary indicator of market exuberance, which can be identified in empirical tests using the "recursive testing procedure" like the right-side unit root test of PWY. This recursive procedure starts with a martingale null (with drift to capture long historical trends in asset data.) The model specification is:

$$y_t = dT^{-n} + \theta_{yt-1} + \epsilon_t \tag{3}$$

where $€_t$ is iid $(0, \sigma^2)$, $\Theta = 1$, and d is a constant, T is the sample size, and the parameter η controls the magnitude of the intercept and the drift, as $T \rightarrow \infty$. Solving eq. 3, gives us the deterministic trend, dt/T^n. The three possibilities here (in sequence) are that if n>0, the drift will be small compared to the linear trend, if n>1/2, the drift is small relative to the martingale and if n=1/2, the output behaves like a Brownian motion, which is evident in many financial time series data.

The emphasis is on the alternative hypothesis because departures from market fundamentals are the markers of interest. Eq. 3 is tested for exuberance using the rolling window ADF approach or the recursive approach. The basic logic is that if the rolling window regression starts from the r_1^{th} fraction and ends with the r_2^{th} fraction (from sample size T), then $r_2 = r_1 + r_w$, where r_w is the size of the window. This model is:

$$\Delta y_t = \propto_{r1,r2} + \beta_{r1,r2}\, y_{t-1} + \Sigma_{i=1}^{k}\, \gamma_{r1,r2}^{i}\, \Delta_{yt-1} + \epsilon_t \tag{4}$$

where k is the lag length, and ϵ_t is iid, with $(0, \sigma^2_{r1,r2})$. They use the Sup ADF test called SADF. It is a recursive / repeated estimation procedure with window size r_w., where r_w goes from r_0 (smallest sample window fraction) to r_1 (largest sample window fraction), and sample end point $r_2 = r_w$, going from 0 to 1. The SADF statistic is:
SADF (r_0) n= $\sup_{r2 \in [r0,1]} ADF^{r2}_0$ (4a)

The ADF regression is run on eq. 4, recursively, but continuously on sub-samples of the data based on window width chosen according to r_0, r_1, r_2……r_w. The subsamples chosen here are more extensive than the SADF test. The difference here is that we allow the window width to change within the feasible range where $r_w = r_2 - r_1$.

The GSADF statistic is:

$$GSADF\ (r_0) = \sup_{\substack{r_2 \in [r_0, 1] \\ r_1 \in [0, r_2 - r_0]}} \{ADF^{r2}_{r1}\} \tag{5}$$

The limit distribution of the GSADF holds, but with the intercept and the assumption of a random walk structure, we have no drift or small drift. The GSADF's asymptotic distribution depends on the "smallest window width size r_0." It depends on the number of observations in the sample. If T is small, r_0 must be made large enough to ensure the inclusion of an adequate number of observations. But, if T is large, r_0 should be set small, to be able to include different "explosive" burst in the data. Simulations in PSY (2014) show that as r_0 decreases, the critical values (CV's, henceforth) of the test statistic increases. GSADF statistic CV's are larger than the SADF statistic, which in turn is larger than the ADF statistic, and its concentration also increases, increasing confidence in the test outcomes. PSY (2015) state "Based on extensive simulation findings, we recommend a rule for choosing r_0 that is based on a lower bound of 1% of the full sample and has the simple functional form $r_0 = 0.01 + 1.8/\sqrt{T}$, which is convenient for implementation. We have, therefore, used this rule in determining the window size. The backward SADF statistic is the sup value of the ADF sequence run over this interval, BSADF r_2 $(r_0) = \sup_{r1 \in [0,\ r2-r0]} \{ADF^{r2}_{r1}\}$.

Empirically we determine the $ADFr_2$ and the sup ADF within the feasible range of r_2 (from r_0 to r_1.) This procedure imposes the condition that the bubble marker is the existence of a critical value greater than L_T = Log (T). This separates the short and temporary market blips (which happen all the time in real life) from actual exuberance. Dating is done using the formula:

$$\hat{r_e} = inf_{r2 \in [r0,1]}\{r_2 : ADF_{r2} > cv^{\beta T}_{r2}\} \tag{6}$$

and

$$\hat{r_f} = inf_{r2 \in [\hat{r_e} + \frac{\log(T)}{T,1}]}\{r_2 : ADF_{r2} < cv^{\beta T}_{r2}\} \tag{7}$$

where $cv^{\boldsymbol{\beta}^T}_{r2}$ is the $100(1-\boldsymbol{\beta}_T)$ % critical value of the ADF statistic based on $[T_{r2}]$ observations. Here $\boldsymbol{\beta}_T \rightarrow 0$, as $T \rightarrow \infty$.

2. Data stamping strategies

The idea is to identify bubbles in real time data and then look for the "markers" identifying those bubbles. The problem is that the standard ADF test can identify extreme observations, as r = [T_r], but cannot separate between a bubble phase observation from one which is part of a natural growth trajectory. Thus, ADF tests may result in finding "pseudo bubble detection." PSY (2014) run backward sup ADF or backward SADF tests, to improve the chances of deciphering a bubble from a growth trajectory. The recursive test means running SADF backwards on the sample, increasing the sample sequence using a fixed sample r_2, but varying the initial point from zero to (r_2-r_0). This gives the SADF statistic: {ADF $^{r2}_{r1}$} ∈|0, r_2 -0|. Bubbles are inferred from the backward SADF statistic or the BSADF $r_2(r_0)$. The origin of the bubbles, the date and timing are the first observation whose BSADF statistic exceeds the critical value of the BSADF. The bubble ending date / period is the first observation whose BSADF is below the BSADF critical value. The intermediary period is the duration of the bubble. The origination / termination dates are calculated thus:

$$\hat{r_e} = inf_{r2\in[r0,1]}\{r_2 \colon BSADF_{r2}(r_0) > scv_{r2}^{\beta T} \tag{8}$$

$$\hat{r_f} = r_{2\in}[inf_{\hat{r_e}+\left[\frac{\partial \log(T)}{T,1}\right]}\{r_2 \colon BSADF_{r2}(r_0) > scv_{r2}^{\beta T} \tag{9}$$

where $scv^{\beta T}_{r2}$ is the 100(1-$\boldsymbol{\beta}_T$)% critical value of the sup ADF statistic, based on [T_{r2}] observations. $\boldsymbol{\beta}_T$ goes to zero, as the sample size approaches infinity. The distinction between the SADF and the GSADF (backward sup ADF) tests, both run over r_2 ∈[r_0,1] is given by the statistic, SADF (r_0) = $\sup_{r2\in[r0,1]}$ {ADF_{r2}} and GSADF (r_0) = $\sup_{r2\in[r0,1]}$ {$BSADF_{r2}(r_0)$. The authors (PSY, 2014) elaborate on the details and derivations of the limit theorems for bubble identification covering all cases, from normal asset price trajectories, i.e., no bubbles to identification of single and most importantly multiple bubbles. The empirical process for detection of multiple bubbles involves more complex dating strategies.

The data stamping process requires calculating $r_{1e,}$ r_{1f}, r_{2e} and r_{2f} from the following equations.

$$\hat{r_{1e}} = inf_{r2\in[r0,1]}\left\{r_2: ADF_{r2} > cv_{r2}^{\beta t}\right\} \quad (10)$$

and

$$\hat{r_{1f}} = inf_{r2\in[\hat{r}_{1e+\frac{\log(T)}{T}},1]}\{r_2: ADF_{r2} < cv_{r2}^{\beta T}\} \quad (11)$$

while

$$\hat{r_{2e}} = inf_{r2\in\left[r_{1f} \quad ,1\right]}\left\{r_2: ADF_{r2} > cv_{r2}^{\beta t}\right\} \quad (12)$$

and

$$\hat{r_{2f}} = inf_{r2\in[r_{2e+\frac{\log(T)}{T}},1]}\left\{r_2: ADF_{r2} < cv_{r2}^{\beta T}\right\} \quad (13)$$

Then we use the backward sup ADF (BSADF) test to calculate the original and termination points based on the following equations.

$$\hat{r_{1e}} = inf_{r2\in[r0,1]}\{r_2: BSADF_{r2}(r_0) > scv_{r2}^{\beta t}\} \quad (14)$$

and

$$\hat{r_{1f}} = inf_{r2\in[\hat{r}_{1e+\frac{\log(T)}{T}},1]}\{r_2: BSADF_{r2}(r_0) < scv_{r2}^{\beta T}\} \quad (15)$$

while

$$\hat{r_{2e}} = inf_{r2\in[\hat{r_{1f}},1]}\{r_2: BSADF_{r2}(r_0) >$$
$$scv_{r2}^{\beta t}\} \quad (16)$$

and

$$\hat{r_{2f}} = inf_{r2\in[\hat{r}_{2e+\frac{\log(T)}{T}},1]}\{r_2: BSADF_{r2}(r_0) < scv_{r2}^{\beta T}\} \quad (17)$$

One could sequentially apply this process detecting one bubble at a time, and then re-applying the same algorithm repeatedly. With continuous re-initialization, the BSADF detector can consistently estimate

$$(\hat{r_{1e}}, \hat{r_{1f,}}, \hat{r_{2e}}, \hat{r_{2f,}}) \xrightarrow{P} (r_{1e}, r_{1f}, r_{1e}, r_{2f}) \quad (18)$$

of the origin and termination points of the first and second bubbles. Both the BSADF and the sequential PWY methodology, provide consistent estimates of the origin and termination of sequential bubbles.

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