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Articles

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The Effect of Noncognitive Factors on Information Disclosure on Social Network Websites: Role of Habit and Affect

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Abstract

Due to the significant role of information disclosure behavior in building social relationships on social network sites, previous studies have examined its determinants, especially from a rational, cognitive perspective. However, emphasis on the cognitive perspective inevitably leads to less attention paid to noncognitive factors despite their implicit and explicit effects on disclosure behavior. To bridge the gap in the literature, we select habit and affect as important noncognitive factors and examine their effect on information disclosure and withdrawal. Our results show that habit significantly motivates information disclosure but restricts information withdrawal. Positive affect toward information disclosure directly and indirectly influences information disclosure through reciprocity, which is an important benefit of disclosure. On the other hand, negative affect exhibits an indirect effect on information withdrawal through privacy risk.

Keywords: habit, affect, information disclosure, noncognitive factors, social network sites

Introduction

In contemporary society, social network (SN) websites such as Facebook have become popular places for social interaction. These social interactions are cultivated by voluntary information disclosure such as sharing personal experiences, activities, photos, or opinions (Posey et al., 2010). As compared to face-to-face settings, the

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disclosure of personal information on SN websites is more extensive in that people publicly reveal their personal information not only to a few intimates but to many others, even those who may be unknown to them (Bazarova and Choi, 2014). Researchers and practitioners have sought to examine important factors that motivate or inhibit information disclosure (Khan, 2017). They commonly examine the antecedents of voluntary information disclosure on SN websites through rational, cognitive perspectives such as the privacy calculus model (Krasnova et al., 2012). According to this perspective, people disclose their personal information when the perceived benefits of information disclosure, such as developing a relationship, exceed the associated costs of disclosure, such as privacy risk (Posey et al., 2010). However, such a rational, cognitive approach tends to overlook the role of noncognitive factors in determining voluntary information disclosure (Yu et al., 2015).

Noncognitive factors such as affect or personality are an important motivator of behavior (Chaiken and Trope, 1999; Triandis, 1989). For example, affect (a feeling state toward an object or behavior) significantly influences behaviors, including the use of technology (Agarwal and Karahanna, 2000), online shopping (Jiang and Benbasat, 2007), and mobile service use (Kim et al., 2007). Despite their implicit and explicit effects on behavior, noncognitive factors and their effects on information disclosure have rarely been examined (Forgas, 2011). In line with Triandis (1989), we select habit and affect as important noncognitive factors that influence information disclosure on SN websites and examine their distinct effects. While habit is defined as a learned sequence of automatic responses to specific situations to obtain certain goals or end states (Verplanken et al., 1997), affect refers to the positive or negative feeling state toward a behavior or object (Slovic et al., 2004). In this study, we examine how habit and affect toward information disclosure influence important privacy behaviors, including information disclosure and withdrawal. While information disclosure indicates the voluntarily sharing of personal information, information withdrawal is defined as withholding information that might otherwise be shared.

Literature Review

Cognitive determinants of information disclosure on SN websites.

In an extensive literature review, Abramova et al. (2017) observe that the rational, cognitive perspective is mainly adopted for examining information disclosure behavior on SN websites and for identifying the associated benefits and costs. Benefits that motivate information disclosure include relationship benefits, the need for affiliation, entertainment, or self-presentation; privacy concerns and privacy risks are representative costs that restrict disclosure behavior.

Information disclosure may be driven by the desire to build a new social relationship, maintain an existing relationship (Chen et al., 2016; Sharif et al., 2021), or attain reciprocity within the community (Walsh et al., 2020). Sharing of personal information facilitates social interactions and develops a close relationship with others (Utz, 2015). Some people disclose their personal information for entertainment purposes. Since SN websites are hedonic in nature, people pursue fun experiences with others by sharing their videos, photos, or events (Krasnova et al., 2012). Self-presentation or expression is also an essential determinant of self-disclosure in SN websites (Chen et al., 2015; Cheung et al., 2015). People formulate positive impressions by presenting desirable information about themselves on SN websites (Krasnova et al., 2010) and reveal personal information to positively enhance or manage their social image (Cheung et al., 2015; Kim and Lee, 2011).

On the other hand, information disclosure on SN websites is impeded by privacy concerns and risk (Gruzd and Hernández-García, 2018). Disclosing personal information inevitably leads to concerns about privacy due to the risk of losing control over one's personal information (Yu et al., 2015).

Habit and information disclosure.

Previous researchers have extensively examined the effects of habit on behaviors such as food consumption or choice (Musarskaya et al., 2018), health behaviors such as hand hygiene or medication adherence (Gardner et al., 2019), and information system use (Venkatesh et al., 2012). However, there has been scant research on the effect of habit on information disclosure. Ko (2013) examines the determinants of continuous information disclosure on journal-type blogs, observing that while habit directly motivates continuous self-disclosure, it also indirectly affects the behavior by amplifying the perceived self and social benefits. Alternatively, some researchers consider information disclosure to be an antecedent of habitual behavior. For example, Lee et al. (2008) suggest a positive effect of information disclosure on the habitual use of blogs. Similarly, Waters and Ackerman (2011) suggest habitual use of social network sites as a consequence of self-disclosure on social networks—that is, disclosing personal information often leads to habitual, involuntary use of social network sites.

Affect and information disclosure.

Previous findings show a meaningful relationship between affect and information disclosure in face-to-face settings (Li et al., 2017). Positive affect toward others leads individuals to evaluate social interactions more optimistically and promotes disclosure of personal information (Yu et al., 2015). Positive affect such as perceived attractiveness or likeness also influences information disclosure in an online setting, suggesting that people are more likely to disclose personal information to those who look attractive (Craig et al., 2007; Posey et al., 2010). On the other hand, Solano et al. (1982) indicate that negative affect such as loneliness is closely associated with a lack of perceived information disclosure to either same-sex or opposite-sex partners. Put another way, people in a positive mood[2] are more likely to disclose intimate, varied, and abstract information about themselves, whereas a negative mood stimulates people to pay more attention to reciprocated information disclosure from their partners in communication (Forgas, 2011).

Hypotheses

Habit develops through repetition in a stable context and guides behavior directly (Limayem et al., 2007). Charng et al. (1988) observe the direct effect of habit on blood donation for regular donors. As people repeatedly donate blood, habit increasingly predicts blood donation, while social norms and attitudes appear as less important factors in predicting donation behavior. Limayem et al. (2003) report a direct positive effect of habit on actual internet-based communication tool usage behavior. Saba et al. (2000) also present habit as an important predictor of actual consumption of high-fat foods. Previous studies demonstrate that behavior becomes routinized as people repeat the behavior, which leads to an automatic response

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[2] Affect and mood are different feeling states. While affect is a feeling state toward a specific object or event, mood indicates feelings that are independent of an object or event (Batson et al., 1992).

that triggers a certain behavior. For example, as the use of an information system becomes routinized, individuals become familiar with the system and use it unconsciously, without cognitive effort (De Guinea and Markus, 2009; Limayem, et al., 2007; Venkatesh et al., 2012). Thus, we hypothesize:

H1: The habit of information disclosure is (a) positively associated with information disclosure on SN websites and (b) negatively associated with information withdrawal on SN websites.

As an intrinsic motivator of behavior, affect directly impacts behavior by creating associations between the outcomes of a behavior and the affective state at the time of undertaking the behavior (Baumeister et al., 2007; Davis et al., 1989). Affect plays an especially important role in interactive behaviors such as communication or relationship development (Forgas, 2011). The constructive nature and indeterminacy of such interactive behaviors may increase the effect of affect on what people do (Forgas, 2011). By anchoring a person's behavior, affect determines their disposition to act and thereby controls behavior. Positive affect is associated with a positive stimulus such as reward and thus is robust to predict a positive consequence or behavior. In contrast, due to its primary association with a negative stimulus, negative affect mainly predicts a negative consequence (Larsen et al., 2001). Consequently, positive affect toward behavior motivates a person to undertake the behavior by perceiving the outcome of behavior optimistically or to repeat the behavior in order to experience the feeling again, while negative affect restricts the behavior by triggering negative consequences or experiences. In the context of this study, positive affect is robust to predict information disclosure, whereas negative affect explains information withdrawal. We posit the following:

H2: (a) Positive affect toward information disclosure is positively associated with information disclosure and (b) negative affect toward information disclosure is positively associated with information withdrawal on SN websites.

Affect often indirectly guides behavior by providing relevant and additional information toward an object or behavior (Finucane et al., 2000). While positive affect promotes a behavior by amplifying benefits or discounting costs associated with it, negative affect restricts a behavior by emphasizing its costs or discounting its benefits (Finucane et al., 2000; Slovic et al., 2004). Accordingly, positive affect toward information disclosure encourages people to reveal their personal information in order to enjoy the benefits of the behavior. In contrast, negative affect toward disclosure demotivates the sharing of personal information by amplifying the costs or risks associated with it.

We select reciprocity and privacy risk as essential positive and negative cognitive evaluations of information disclosure. While reciprocity is defined as a mutually contingent exchange of personal information (Altman and Taylor, 1973), privacy risk refers to the expectation that a high potential for loss of privacy is associated with the release of personal information to others (Malhotra et al., 2004). Positive affect encourages information disclosure to others in SN websites by amplifying expected reciprocity. On the other hand, negative affect increases the perceived risk of information disclosure, which leads to the withdrawal of information. In addition, we suggest a greater effect of positive affect on information disclosure than that of negative affect on information withdrawal due to greater reliance on the systematic, cognitive evaluation of a negative stimulus. People tend to rely more on cognitive evaluations to inform their behavior because negative consequences are perceived as more important than positive outcomes (Alves et al., 2017). In this light, the direct effect of affect on information disclosure would be greater for information disclosure than withdrawal. We propose:

H3: (a) Positive affect toward information disclosure is positively associated with reciprocity, and (b) negative affect toward information disclosure is positively associated with privacy risk.
H4: (a) Reciprocity is positively associated with information disclosure in SN websites, and (b) privacy risk is positively associated with information withdrawal.
H5: The effect of positive affect on information disclosure is greater than the effect of negative affect on information withdrawal.

Our research model is illustrated in Figure 1

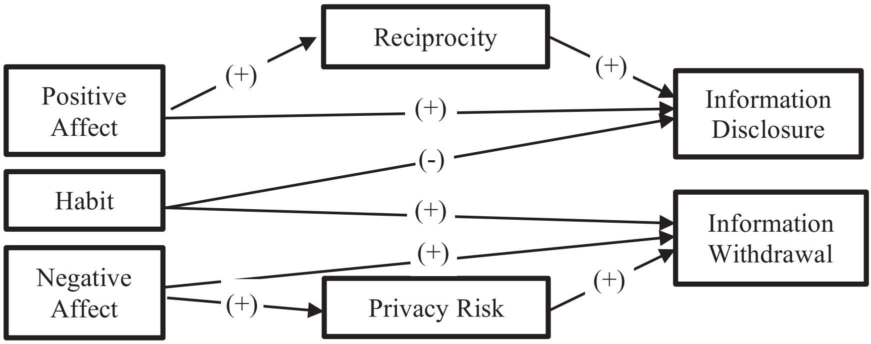

Figure 1. Research Model

Study Design and Data

Research Design

We collected data from more than 100 undergraduate students in business courses at a large U.S. university. To collect data, we contacted instructors who taught the classes to invite their students to participate in the survey. To minimize self-selection bias, we visited the classes without prior notice to students and asked them to voluntarily participate in data collection after explaining the study's objectives and possible risks and benefits of the study. We started data collection when all of the students in a class agreed to participate. In all classes, all attending students voluntarily participated in data collection, suggesting that students took part in this study regardless of their interest in the topic of the study. Each participant provided some demographic information such as age and gender, indicated their information disclosure and withdrawal behavior, and answered questions regarding their habits of information disclosure, positive and negative affect toward information disclosure, and perceived benefits (reciprocity) and risks (privacy risk).

Measures

We adopted previously validated question items for measuring each investigated construct and adapted them with minor word changes to better fit our participants and context. We measured the habit of information disclosure with items from Verplanken and Orbell (2003). We used items to measure information disclosure and withdrawal from Limayem et al. (2007) and Yu et al. (2015). Positive and negative affect toward information disclosure, reciprocity, and privacy risk were measured with items from Yu et al. (2015). All question items employed a 7-point Likert scale anchored with 1 = “strongly disagree” and 7 = “strongly agree.”

Analyses and Results

We approached 140 students enrolled in business courses for their voluntary participation; among them, 114 agreed to take part in the study, excepting students absent in the classes, for an effective response rate of 81.4%. As shown in Table 1, approximately 48.0% of the participants were females, and about 81.4% were younger than 25 years of age.

Table 1. Descriptive Statistics

Measure	Value	Number (%)
Gender	Male	55 (48.0%)
	Female	59 (52.0%)
Age	< 20	11 (9.7%)
	20-24	81 (71.7%)
	25-29	13 (11.5%)
	> 30	8 (7.1%)

Measure Assessments

We assessed our measures in terms of construct reliability and convergent and discriminant validity. To establish indicator reliability, we first removed items with a loading value equal to or lower than 0.7 (Götz et al., 2010). We then examined construct reliability based on Cronbach’s alpha and composite reliability, using the common threshold of 0.7 (Bagozzi and Yi, 1988). As we summarize in Table 2, each construct showed composite reliability greater than the threshold, suggesting appropriate construct reliability, meaning that the items for a construct measured the same concept. We evaluated convergent validity by examining average variance extracted (AVE), using the common threshold of 0.5 (Götz et al., 2010). We assessed discriminant validity in terms of the square roots of AVEs and the pair-wise correlations between constructs (Fornell and Larcker, 1981). In general, we consider appropriate discriminant validity to be established when a construct's square root of AVE is significantly greater than the correlation between a pair of constructs. As we show in Tables 2 and 3, the AVE value of each construct exceeded 0.5 and was considerably greater than the correlations between any pair of constructs. In addition, we compared the loading values of each construct with those of other constructs, and the results showed adequate discriminant validity. Together, our results indicate adequate convergent and discriminant validity of the measures.

Table 2. Analysis of Construct Reliability

	Mean (Standard Deviation)	Cronbach alpha	Composite Reliability	AVE
Habit of ID	2.66 (1.55)	0.939	0.948	0.623
Positive affect toward ID	3.27 (1.61)	0.811	0.874	0.636
Negative affect toward ID	4.44 (1.65)	0.792	0.877	0.704
Reciprocity	3.23 (1.67)	0.748	0.888	0.798
Privacy risk	5.73 (1.38)	0.914	0.945	0.853
Information disclosure	2.29 (1.41)	0.861	0.899	0.641
Information withdrawal	4.92 (1.57)	0.874	0.907	0.662

Note: ID = Information disclosure; AVE = Average variance extracted

Table 3. Square Roots of AVE and Correlations between Constructs

	HABT	IDB	IWB	PAID	NAID	RECP	RISK
HABT	0.789						
IDB	0.690	0.801					
IWB	-0.327	-0.423	0.813				
PAID	-0.371	-0.424	0.393	0.839			
NAID	0.494	0.503	-0.345	-0.419	0.797		
RECP	0.509	0.388	-0.185	-0.232	0.341	0.893	
RISK	-0.202	-0.288	0.402	0.455	-0.207	-0.183	0.923

Note: HABT = Habit of information disclosure; IDB = Information disclosure behavior; IWB = Information withdrawal behavior; PAID = Positive affect toward information disclosure; NAID = Negative affect toward information disclosure; RECP = Reciprocity; RISK = Privacy risk.

We assessed the multicollinearity of our measurement items by examining the variance inflation factor (VIF). We used the threshold of 3.3 (Cenfetelli and Bassellier, 2009) that is recommended in the context of variance-based structural equation models (Kock and Lynn, 2012). All VIF values were below the threshold, suggesting that multicollinearity is not a serious problem in our data.

Hypothesis Test Results

We applied partial least squares-structural equation modeling (PLS-SEM) to analyze the data using SmartPLS3. PLS enables the estimation of constructs and structural paths without imposing distributional assumptions and predictions in estimating statistical models which are designed to provide causal explanations (Hair et al., 2019). As shown in Table 4, habit was positively associated with information disclosure but had a negative effect on information withdrawal. Thus, our data supported H1(a) and H1(b).

Positive affect toward information disclosure had a significant positive effect on information disclosure, in support of H2(a). However, the effect of negative affect on information withdrawal was marginal. Thus, our data did not support H2(b).

Positive affect and negative affect were significantly associated with reciprocity and privacy risk, respectively, in support of H3(a) and H3(b).

While reciprocity had a marginal effect on information disclosure, privacy risk was positively associated with information withdrawal. So, our data supported H4(a), but not H4(b).

Table 4. Hypothesis Test Results of Direct and Indirect Ambivalent Model

Exogenous	Endogenous	Path Coefficient	Hypothesis	Result
HABT	IDB	0.534^{***} (0.08)	H1(a)	Supported
	IWB	-0.231^{*} (0.10)	H1(b)	Supported
PAID	IDB	0.224^{*} (0.10)	H2(a)	Supported
	RECP	0.333^{***} (0.09)	H3(a)	Supported
NAID	IWD	0.185 (0.13)	H2(b)	Not supported
	RISK	0.435^{***} (0.11)	H3(b)	Supported
RECP	IDB	0.039 (0.10)	H4(a)	Not supported
RISK	IWD	0.270^{*} (0.11)	H4(b)	Supported

Age	IDB	-0.000 (0.07)	Control variable
	IWD	-0.160 (0.15)	
Gender	IDB	-0.000 (0.07)	
	IWD	-0.041 (0.09)	

Note: HABT = Habit of information disclosure; IDB = Information disclosure behavior; IWB = Information withdrawal behavior; PAID = Positive affect toward information disclosure; NAID = Negative affect toward information disclosure; RECP = Reciprocity; RISK = Privacy risk, values in parenthesis indicate standard error, *p < 0.05, **p < 0.01, ***p < 0.001

To compare the effects of positive and negative affect on privacy behavior, we analyzed the effect of positive affect on information disclosure and that of negative affect on information withdrawal separately after removing other factors. The significant effect of positive affect and the marginal effect of negative affect seem to support H5. In addition, the z-test result from comparing the coefficients suggests that the effect of positive affect is significantly greater than that of negative affect.

We compared the magnitudes of the path coefficients of positive and negative affect and tested if positive affect has a greater effect using a two-tailed *t*-test, in line with Steelman et al. (2014)[3]. These path coefficients as the parameters of the model represent connection strengths or estimates of effective connectivity. As shown in Table 5, the path coefficient of positive affect is significantly greater than that of negative affect, indicating a greater impact of positive affect on information disclosure than of negative affect on information withdrawal.

Table 5. Comparison of the Effect of Positive and Negative Affect

Affect	Privacy Behavior	Path Coefficient	*t*-value	Hypothesis
Positive Affect	Information Disclosure	0.520 (0.07)***	10.96***	H5 (Supported)
Negative Affect	Information Withdrawal	0.403 (0.09)***		

*p < 0.05, **p < 0.01, ***p < 0.001

[3] $t = \dfrac{Coefficient_{sample\_1} - Coefficient_{sample\_2}}{\left[\sqrt{\frac{(m-1)^2}{(m+n-2)} \times S.E.^2_{sample_1} + \frac{(m-1)^2}{(m+n-2)} \times S.E.^2_{sample_2}}\right] \times \left[\sqrt{\frac{1}{m}+\frac{1}{n}}\right]}$

Discussion and Conclusion

In this study, we examine how two representative noncognitive factors, habit and affect, influence information disclosure and withdrawal in SN websites. The findings have several implications. Our results suggest the necessity of considering information disclosure and withdrawal as distinct and separate constructs that have their own antecedents. While the effect and consequence of information disclosure are highlighted in many previous studies, information withdrawal seems to deserve more attention. From the perspective of firms or online vendors, it is particularly important to know why people hesitate to offer their personal information online because information withdrawal would limit their knowledge of customers and reduce their competitive advantage.

Second, our results show a marginal direct effect of negative affect on information withdrawal, different from the significant direct effect of positive affect on information disclosure. This result may suggest that information withdrawal is more likely to be influenced by cognitive evaluation than information disclosure. That is, people tend to rely on positive affect in deciding about information disclosure but consider cognitive evaluation more when withdrawing personal information. For a better understanding of how people decide between information disclosure and withdrawal, it is important to examine the relationship between affect and cognitive evaluation.

Finally, the results also confirm the indirect effect of affect through cognitive factors. Positive affect toward information disclosure amplifies perceived reciprocity and negative affect augments the perception of privacy risk. Affect directly guides important privacy behavior, but also impacts the behavior by influencing relevant cognitive factors.

Our study has some limitations. First, we collected data from university students. Thus, the generalizability of our findings is limited. Future researchers can improve generalizability by collecting data from a broader sample. Second, the sample size is small. Although we applied a bootstrapping method to get more accurate results, a larger sample will lead to more robust results. Third, we consider a few cognitive evaluations associated with information disclosure and withdrawal. Future researchers can employ more evaluations such as self-presentation or entertainment to examine how affect and cognitive evaluation jointly influence privacy behavior.

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Betting That the Market is Not Efficient: A Note

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The task of deciding how long a security must be held before judging whether its return is anomalous or not has left the efficient market hypothesis somewhat in limbo. Are six months sufficient? Is a one-year period better? Would two years be too long? Pankoff (1968) offered a solution to definitive testing of efficient behavior. He argued that the football-betting market is no less efficient that the securities market owing to the numerous, knowledgeable, competitive and profit-maximizing bettors that discount all available information and reduce the outcomes of bets to random chance. But unlike stocks, bets can be evaluated simply and decisively: at the conclusion of games. When Pankoff tracked the performance of home teams in the National Football League (NFL) against the spread between 1956 and 1965, he broke even and concluded that the football betting market is efficient.

Many researchers have used the analogy to test the efficient market hypothesis albeit more creatively. Gray and Gray (1997) placed imaginary wagers *on* teams in the NFL who met three conditions making them appear underperforming and undervalued by bettors. The contrarian strategy generated above-average returns. That tendency of point spreads to adjust superficially to bettors' beliefs encouraged Kochman (2000) to hypothesize that point spreads in games involving reigning Super Bowl champions would be inflated or deflated to the detriment of those who bet *on* them to beat the spread and to the advantage of those betting *against* them. Again, above-average returns were achieved when Kochman bet *against* the previous year's Super Bowl winner in the first five games of the following year during the 1987-1997 seasons.

The mistake by some of betting on a team's past success was termed a "sticky preference" by Fodor et al. (2013). They found that bets *on* teams in the NFL during the opening week of the season that had qualified for the playoffs in the prior year recorded a losing wins-to-bets ratio of 35.6 percent over the 2004-2012 seasons. The authors reasoned that bettors mistakenly cling to perceptions of teams they had formed previously and fail to update valuations—hence, the "holdover effect".

Kochman et al. (2016) investigated the holdover bias by placing imaginary wagers *against* last season's playoff teams in the NFL during the entire new season. When they generated a wins-to-bets ratio of 49.2 percent during the 2004-2013 seasons, Kochman et al. concluded that bettors had discovered, acted upon and driven out the early-season anomaly reported by Fodor et al.

Bennett (2019) examined the holdover effect in college football during the 2008-2016 seasons. He found that betting *against* the teams in the first game of the season who had ranked in the past year's Associated Press Top 25 Poll won at a rate greater than the breakeven mark and decidedly greater for wagers *against* the prior season's top 10. The author concluded that the inefficiency could be attributed to the backward-looking of bettors as well as reliance on outdated information.

Another way to evaluate the holdover bias is to reconsider Kochman's (2000) "Super Bowl effect" since it too keys on past successes. Like Kochman, we placed wagers *against* reigning Super Bowl winners also believing that point spreads were unduly inflated or deflated; but unlike Kochman, we made those bets season-long vis-à-vis the first five games. Specifically, we bet *against* the 31 reigning Super Bowl champions during the 1990-2020 period. That contrarian strategy generated a wins-to-bets ratio of 46.6 percent. See Table 1. Since typical odds of $11-to-win-$10 produce a breakeven rate of 52.4 percent (or 11/21), the obverse scheme of betting *on* reigning Super Bowl winners would have proven profitable with a W/B ratio of 53.4 percent. When the table is divided by recency, two different cumulative W/B ratios emerge. Betting *against* reigning winners during the 1990-2009 period led to a rate of 48 percent while the rate for 2010-2020 dropped to 45 percent. The profitable return of 55 percent when betting *on* reigning Super Bowl winners over the final 11 years of our study serves to refute the efficient market hypothesis and its assumption that regular profit-taking is not possible.

Our results have separate meanings for those individuals touched by sports betting. For the professional bettor, betting *against* reigning Super Bowl winners seems to generate early-season gains that transform into losses as the market overcorrects its error and makes wagers *on* Super Bowl champions a profitable strategy by season's end. For the recreational bettor, wins and losses have less significance. Conducting research, placing bets and checking results provide entertainment win or lose. For the academic, the numbers confirm what is often said about competitive markets: profit opportunities can occur but are generally corrected (or overcorrected) with dispatch. For us, we were able to apply behavioral finance to the real world—i.e., the belief that financial decisions are sometimes made irrationally. Beating the average bettor who behaves irrationally accounts for the positive returns in the early weeks of the football season and some toward the end. Beating the market, on the other hand, was less imagined. In a whimsical way, that perspective is reminiscent of a clever TV commercial where an antelope stutteringly warns his companion of a feline predator and that a certain energy drink will not allow him to outrun the lion to which his friend calmly responds that he only has to run faster than him—not the lion.

Table 1
W/B ratios when betting *against* the reigning Super Bowl winner (1990-2020)

Year bet	Reigning winner	Wins	Bets	W/B	Year bet	Reigning winner	Wins	Bets	W/B
1990	San Francisco	8	18	44.4%	2006	New England	7	19	36.8%
1991	San Francisco	8	16	50.0%	2007	Pittsburgh	8	17	47.1%
1992	NY Giants	5	16	31.3%	2008	Indianapolis	8	16	50.0%
1993	Washington	5	15	33.3%	2009	NY Giants	10	16	62.5%
1994	Dallas	9	18	50.0%	2010	Pittsburgh	7	19	36.8%
1995	Dallas	10	19	52.6%	2011	New Orleans	5	18	27.8%
1996	San Francisco	9	17	52.9%	2012	Green Bay	8	18	44.4%
1997	Dallas	3	15	20.0%	2013	NY Giants	9	16	56.3%
1998	Green Bay	7	15	46.7%	2014	Baltimore	8	17	47.1%
1999	Denver	9	14	64.3%	2015	Seattle	9	17	52.9%
2000	Denver	9	17	52.9%	2016	New England	3	19	15.8%
2001	St. Louis	10	18	55.6%	2017	Denver	11	15	73.3%
2002	Baltimore	10	16	62.5%	2018	New England	7	19	36.8%
2003	New England	5	19	26.3%	2019	Philadelphia	10	17	58.8%
2004	Tampa Bay	9	14	64.3%	2020	New England	9	16	56.3%
2005	New England	9	18	50%	1990-2009		135	282	48.0%
					2010-2020		109	242	45.0%
					1990-2020		244	524	46.6%

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How Big is the Tax Subsidy of Home Mortgage Loans?

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Abstract

Tax subsidy of home mortgage loans has been suggested as one of the motivations people to buy a home. This study provides a closed form solution to estimate how big it is. This formula is very much usable to assess the size of tax benefits of home mortgage loans since all the inputs needed are available publicly or in the mortgage contracts. Based on average mortgage amount each year, interest rate and tax rate, this study presents size of tax subsidy of home mortgage loans in U.S.

Introduction

With mounting national debt over the years and difficulty in finding new sources of tax revenues to meet the spending budget, political arena has been discussing the possibility of reducing or eliminating this tax benefit of the home mortgage loans.[1] Most people expect an uphill fight in this effort. This discussion on tax benefit of the home mortgage loans in political realm has spawned public's interest in the issue.

Historically, home buyer's tax credit on home mortgage loans has long been used as one of the justifications to buy a home rather than to rent.[2] For many, the size of the personal income tax reducing effect of interest expenses on home mortgage loans can be thought of as a good incentive to buy a house. With high inflation, this benefit could be expanded because the effective cost of homeownership could be significantly reduced under high inflation as Poterba (1984)

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[1] Bair, S. (2013). Will Congress Have the Guts to Kill the Home Mortgage Deduction?. *Fortune*, *167*(4), 94.
[2] Esswein, P. (2010). Should you buy or rent?. *Kiplinger's Personal Finance*, *64*(4), 73-74.

showed in a theoretical formulation and a simulation. His explanation is especially useful in explaining the housing booms during 1970, when the inflation was very high. However, with significantly reduced personal income tax rate and rather controlled level of inflation over last three decades, anyone could imagine significantly reduced tax benefits of a home mortgage loans. Beracha and Johnson (2012) and Voice and Seiler (2013) show that from the housing data during the last three decades, this has been precisely the case.

Of course, there will be a lot of factors that affect people's decision to buy a home or rent. Unfortunately, many of them are not measurable. For example, some home buyers would value increased privacy, uninterrupted family time, gardens and yards etc. to name a few. However, the effect of these on home buying decision is very difficult to quantify.

This study seeks to quantify the tax benefits of home mortgage loans to see how big the tax subsidy of home mortgage loan is. In most finance texts, examples of typical mortgage loan amortizations are illustrated in a excel example format. While amortization schedule of a mortgage loan can be easily set up in excel, finding the present value of tax benefits of home mortgage loans cannot be visualized quickly enough.

The current study presents a closed form formula to find tax benefits of home mortgage loans. With this closed form formula, anyone with the set of inputs, can quickly estimate the present value of all future tax benefits from a given home mortgage loan. This is exactly the area this study intends to contribute to.

Model

Let's suppose we would like to estimate the present value of tax subsidy of home mortgage loans. Let P_0 denote the principal amount in the loan, I the monthly interest rate (i.e. APR/12), F fixed monthly interest payment, n the number of monthly periods in the loan. Then total interest payments will be calculated as[3]

$$\sum_{k=1}^{n} Monthly\ Interest\ Payments$$

$$= P_0 I + [\,P_0(1+I) - F]I + \big[P_0(1+I)^2 - F[1+(1+I)]\big]I + \cdots$$
$$+ \left[P_0(1+I)^{n-1} - F\left[\frac{(1+I)^{n-1}-1}{I}\right]\right] I$$

It follows that the present value of tax subsidy of interest payments over the life of the loan is calculated as

$$\sum_{k=1}^{n} PV\ of\ Tax\ Subsidy\ of\ Monthly\ Interest\ Payments$$

$$= \frac{P_0 IT}{1+y} + \frac{[\,P_0(1+I) - F]IT}{(1+y)^2} + \frac{\big[P_0(1+I)^2 - F[1+(1+I)]\big]IT}{(1+y)^3}$$
$$+ \cdots$$
$$+ \frac{\big[P_0(1+I)^{n-1} - F[1+(1+I)+(1+I)^2+\cdots+(1+I)^{n-2}]\big]IT}{(1+y)^n}$$

$$= \frac{P_0 IT}{y-I}\left[1 - \left(\frac{1+I}{1+y}\right)^n\right]$$
$$- FT\left[\frac{I}{y(y-I)} - \frac{1}{(1+y)^n}\left[\frac{(1+I)^n}{y-I} + \frac{1}{y}\right]\right]$$

, where y is the monthly opportunity cost of home owners.

Illustration

Suppose a 30-year mortgage with principal \$200,000, APR 4.3% (average APR on 30-year conventional mortgage today), personal income tax rate 10%, monthly fixed payment of \$643.279, monthly opportunity cost of 4.56% (most recent yield on mortgage bond index).

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[3] Detailed derivations of these equations are presented in the appendix. PV of interest payments are calculated similarly and available on request.

Then the present value of tax subsidy of this loan over the life of the loan will be

$$\frac{200{,}000 * \frac{0.043}{12} * 0.1}{\frac{0.0456}{12} - \frac{0.043}{12}}\left[1 - \left(\frac{1 + \frac{0.043}{12}}{1 + \frac{0.0456}{12}}\right)^{360}\right] - 643.279 * 0.1$$
$$* \left[\frac{\frac{0.043}{12}}{\frac{0.0456}{12}\left(\frac{0.0456}{12} - \frac{0.043}{12}\right)} - \frac{1}{\left(1 + \frac{0.0456}{12}\right)^{360}}\left[\frac{\left(1 + \frac{0.043}{12}\right)^{360}}{\frac{0.0456}{12} - \frac{0.043}{12}} + \frac{1}{\frac{0.0456}{12}}\right]\right]$$
$$= 24731.67221 - 14.75714 = 24716.91507$$

Size of tax subsidy of home mortgage loans for average U.S. household[4]

Figures 1, 2, and 3 show time series of present value of interest payments, present value of tax subsidy, and the ratio of present value of tax subsidy to present value of interest payments for average U.S. home owners for the period 1974 – 2013. In figure 1, present value of interest payment has changed from $28,610 in 1974, peaked at $161,815 in 2006 and back to $120,043 in 2013. In figure 2, present value of tax subsidy has also changed $4,048 in 1974 and peaked $21,950 in 2006 and to $15,569 in 2013. While figures 1 and 2 show that present value of interest payments and present value of tax subsidy have changed in a similar up trend, figure 3 shows that ratio of present value of tax subsidy to present value of interest payments for average U.S. home owners experienced a general down trend.

[4] Average personal income tax rate information is from http://www.taxpolicycenter.org/taxfacts/displayafact.cfm?Docid=228
Historical mortgage rates and yields on those were obtained from http://www.freddiemac.com/pmms/pmms30.htm
Average house price is from http://www.census.gov/construction/nrs/pdf/uspricemon.pdf

Most recent years' ratios of present value of tax subsidy to present value of interest payments for average U.S. home owners have been around 12% compared to peak 18.4% in 1981. This indicates that the merit of tax subsidy of home mortgage has declined over time and is smaller than what many people think it is.

Conclusion

Traditionally tax subsidy of home mortgage loans has been suggested as one of the most important motivations of buying a home rather than rent. This study shows how present value of tax subsidy from a home mortgage loan can be calculated in a closed form solution format. Present value of tax subsidy of home mortgage loans calculated from the closed form solution given in this study can be used in the decision-making process of home buying. Illustration using average mortgage amount each year, interest rate and tax rate average U.S. households indicates the merit of tax subsidy of mortgage loans has been declined significantly.

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Appendix

Generalized Amortization Schedule of Home Mortgage Loans

	Principal	Monthly Payment	Monthly Interest	Payment for Principal	Remaining Principal
1	P_0	F	$P_0 I$	$F - P_0 I$	$P_0(1+I) - F$
2	$P_0(1+I) - F$	F	$[\,P_0(1+I) - F]I$	$F - [\,P_0(1+I) - F]I$	$P_0(1+I)^2 - F[1+(1+I)]$
3	$P_0(1+I)^2$ $- F[1+(1+I)]$	F	$\left[P_0(1+I)^2 - F[1+(1+ I)]\right]I$	$F - \left[P_0(1+I)^2 - F[1+(1+I)]\right]I$	$P_0(1+I)^3 - F[1+(1+I)) + (1+I)^2]$
⋮	⋮	⋮	⋮	⋮	⋮
n	$P_0(1+I)^{n-1}$ $-F[1+(1+I)$ $+(1+I)^2+\cdots$ $+(1+I)^{n-2}\,]$ $= P_0(1+I)^{n-1}$ $- F\left[\frac{(1+I)^{n-1} -}{I}\right.$	F	$\left[P_0(1+I)^{n-1} - F\left[\frac{(1+I)^{n-1}-1}{I}\right]\right]I$	$F - \left[P_0(1+I)^{n-1} - F\left[\frac{(1+I)^{n-1}-1}{I}\right]\right]I$	$P_0(1+I)^n - F[1+(1+I)) + (1+I)^2 + \cdots + (1+I)^{n-1}]$ $= \frac{(1+I)^n - 1}{(1+I) - 1}$ $= \frac{(1+I)^n - 1}{I}$

$$\sum_{k=1}^{n} Monthly\ Interest\ Payments$$
$$= P_0 I + [\,P_0(1+I) - F]I + \big[P_0(1+I)^2 - F[1+(1+I)]\big]I + \cdots + \left[P_0(1+I)^{n-1} - F\left[\frac{(1+I)^{n-1}-1}{I}\right]\right]I$$

The Present Value for the Interest Payments in Consideration of Tax Payments

$$\sum_{k=1}^{n} Monthly\ Interest\ Payments$$
$$= \frac{P_0 IT}{1+y} + \frac{[\,P_0(1+I) - F]IT}{(1+y)^2} + \frac{\big[P_0(1+I)^2 - F[1+(1+I)]\big]IT}{(1+y)^3} + \cdots$$
$$+ \frac{\big[P_0(1+I)^{n-1} - F[1+(1+I)+(1+I)^2+\cdots+(1+I)^{n-2}]\big]IT}{(1+y)^n}$$

$$
\begin{aligned}
&= \frac{P_0IT}{1+y} + \frac{P_0IT(1+I)}{(1+y)^2} + \frac{P_0IT(1+I)^2}{(1+y)^3} + \cdots + \frac{P_0IT(1+I)^{n-1}}{(1+y)^n} \\
&\qquad - \left[\frac{FIT}{(1+y)^2} + \frac{FIT[1+(1+I)]}{(1+y)^3} + \frac{FIT[1+(1+I)+(1+I)^2]}{(1+y)^4} + \cdots \right. \\
&\qquad \left. + \frac{FIT[1+(1+I)+(1+I)^2+\cdots+(1+I)^{n-2}]}{(1+y)^n}\right] \\
&= \frac{P_0IT}{1+y}\left[1 + \frac{1+I}{1+y} + \left(\frac{1+I}{1+y}\right)^2 + \cdots + \left(\frac{1+I}{1+y}\right)^{n-1}\right] \\
&\qquad - \frac{FIT}{(1+y)^2}\left[1 + \frac{1+(1+I)}{(1+y)} + \frac{1+(1+I)+(1+I)^2}{(1+y)^2} + \cdots \right. \\
&\qquad \left. + \frac{1+(1+I)+(1+I)^2+\cdots+(1+I)^{n-2}}{(1+y)^{n-2}}\right] \\
&= \frac{P_0IT}{1+y}\left[1 + \frac{1+I}{1+y} + \left(\frac{1+I}{1+y}\right)^2 + \cdots + \left(\frac{1+I}{1+y}\right)^{n-1}\right] \\
&\qquad - \frac{FIT}{(1+y)^2}\left[1 + \frac{1+(1+I)}{(1+y)} + \frac{1+(1+I)+(1+I)^2}{(1+y)^2} + \cdots + \frac{(1+I)^{n-1}-1}{I(1+y)^{n-2}}\right]
\end{aligned}
$$

$$
\begin{aligned}
&1+\frac{1+I}{1+y}+\left(\frac{1+I}{1+y}\right)^{2}+\cdots+\left(\frac{1+I}{1+y}\right)^{n-1}\\
&=\sum_{k=1}^{n}\left(\frac{1+I}{1+y}\right)^{k-1}\\
&=\frac{1-\left(\frac{1+I}{1+y}\right)^{n}}{1-\frac{1+I}{1+y}}\\
&=\frac{(1+y)\left[1-\left(\frac{1+I}{1+y}\right)^{n}\right]}{(1+y)-(1+I)}\\
&=\frac{(1+y)\left[1-\left(\frac{1+I}{1+y}\right)^{n}\right]}{y-I}\\
&=\frac{1+y}{y-I}\left[1-\left(\frac{1+I}{1+y}\right)^{n}\right]
\end{aligned}
$$

$$1+\frac{1+(1+I)}{(1+y)}+\frac{1+(1+I)+(1+I)^2}{(1+y)^2}+\cdots+\frac{(1+I)^{n-1}-1}{I(1+y)^{n-2}}$$

$$=\sum_{k=1}^{n}\frac{(1+I)^{n-1}-1}{I(1+y)^{n-2}}$$

$$=\frac{1+I}{I}\sum_{k=1}^{n}\left(\frac{1+I}{1+y}\right)^{k-2}-\frac{1}{I}\sum_{k=1}^{n}\left(\frac{1}{1+y}\right)^{k-2}$$

$$=\frac{1+I}{I}\left(\frac{1+I}{1+y}\right)^{-1}\frac{1-\left(\frac{1+I}{1+y}\right)^{n}}{1-\left(\frac{1+I}{1+y}\right)}-\frac{1}{I}\left(\frac{1}{1+y}\right)^{-1}\frac{1-\left(\frac{1}{1+y}\right)^{n}}{1-\frac{1}{1+y}}$$

$$=\frac{(1+y)^2}{I}\frac{1-\left(\frac{1+I}{1+y}\right)^{n}}{y-I}-\frac{(1+y)^2}{I}\frac{1-\left(\frac{1}{1+y}\right)^{n}}{y}$$

$$=\frac{(1+y)^2}{I}\left[\frac{1}{y-I}\left[1-\left(\frac{1+I}{1+y}\right)^{n}\right]-\frac{1}{y}\left[1-\left(\frac{1}{1+y}\right)^{n}\right]\right]$$

$$=\frac{P_0IT}{1+y}\frac{1+y}{y-I}\left[1-\left(\frac{1+I}{1+y}\right)^{n}\right]-\frac{FIT}{(1+y)^2}\frac{(1+y)^2}{I}\left[\frac{1}{y-I}\left[1-\left(\frac{1+I}{1+y}\right)^{n}\right]-\frac{1}{y}\left[1-\left(\frac{1}{1+y}\right)^{n}\right]\right]$$

$$= \frac{P_0 IT}{y-I}\left[1-\left(\frac{1+I}{1+y}\right)^n\right] - FT\left[\frac{1}{y-I}\left[1-\left(\frac{1+I}{1+y}\right)^n\right] - \frac{1}{y}\left[1-\left(\frac{1}{1+y}\right)^n\right]\right]$$

$$= \frac{P_0 IT}{y-I}\left[1-\left(\frac{1+I}{1+y}\right)^n\right] - FT\left[\frac{I}{y(y-I)} - \frac{1}{y-I}\left(\frac{1+I}{1+y}\right)^n + \frac{1}{y}\left(\frac{1}{1+y}\right)^n\right]$$

$$= \frac{P_0 IT}{y-I}\left[1-\left(\frac{1+I}{1+y}\right)^n\right] - FT\left[\frac{I}{y(y-I)} - \frac{1}{(1+y)^n}\left[\frac{(1+I)^n}{y-I} + \frac{1}{y}\right]\right]$$

Figure 1. PV of Interest Payments for average U.S. home owners: 1974 - 2013

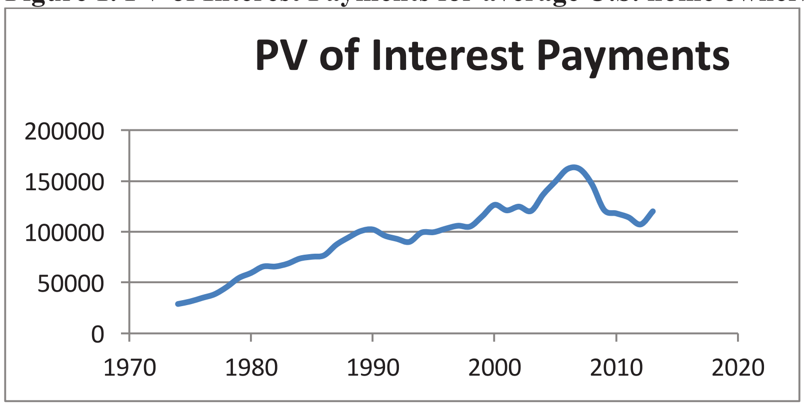


Figure 2. PV of Tax Subsidy for average U.S. home owners: 1974 – 2013

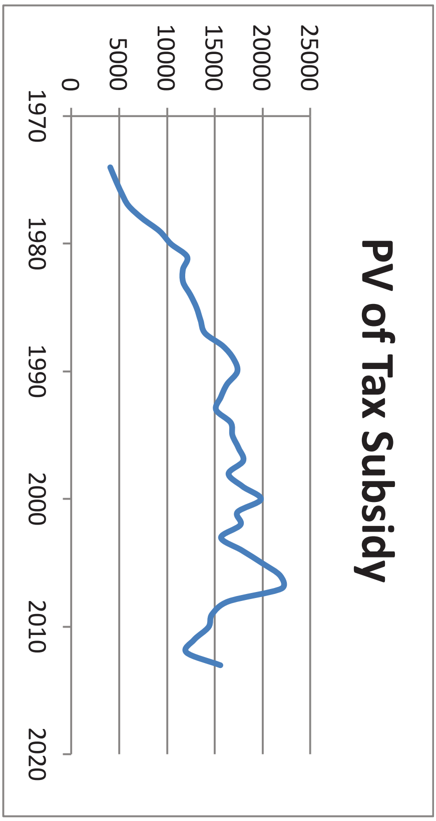
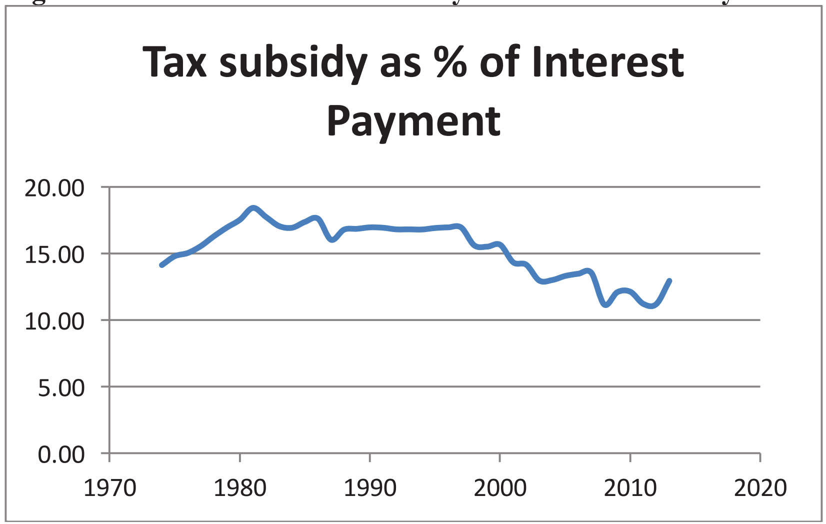


Figure 3. Ratio of PV of Tax Subsidy to PV of Interest Payments: 1974 – 2013



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