Mobile Commerce and Device Specific Perceived Risk

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Abstract

This study examines the role of perceived risk and access device type on consumers' on-line purchase decisions. We use a two-step hurdle approach to estimate consumer behavior. In the first step, the decision of whether to engage in eCommerce is estimated and in the second step, how many orders to place is estimated. We use a large multi-year survey sample of households from Canada's national statistical agency—Statistics Canada. The sample size is such that we are able to conduct sub-sample analysis of PC-only users, mobile-only users, and other-users. We show that online security and price significantly influence mobile eCommerce. We also show that there is a statistically significant difference in the intensity of eCommerce engagement across device type and consumer risk type (high / low). One of our main findings is that perceived risk affects purchase decisions for mobile users more than PC users, however additional comparisons are carried out with our analysis.

1. Introduction

Ecommerce constitutes 5.9% of the world-wide retail market, accounting for a total expenditure of $1.32 trillion dollars, with the US and China accounting for the largest volume [1, 2]. In Canada, eCommerce was $15.26 billion in 2010 and $18.93 billion in 2012 [3]. Ecommerce is expected to grow at a year over year rate of 17% [1] in the US, yet to maintain this growth rate eSellers should understand the impact of perceived transactions risk on consumer behavior. In particular, with recent security breaches at Sony and Home Depot [4], an increase in perceived risk may indeed be warranted. Undoubtedly, consumers may curtail their purchasing behavior when confronted with unfavorable media reports. In addition to data breaches, consumers may be concerned about phishing websites, identity theft, and credit-card theft when making an online purchase. For example, wealthy Africans distrust eCommerce [5].

In this paper we contribute to the literature that addresses the research problem of characterizing and analyzing the impact of perceived risk on eCommerce. In order to contribute to the literature we will examine the following research questions: 1. **Does an individual's perceived risk of eCommerce affect their actions, when accounting for access device type?** 2. **Is the impact of perceived risk on the intensity of eCommerce purchases the same across male and female consumers?** We will first look at the impact of access device types on eCommerce because the propensity to use mobile devices for eCommerce is increasing. For example, in 2014 it was estimated that 24% of eCommerce purchases in the United Kingdom were made with mobile devices, and that fraction is expected to reach 35% by 2017 [1]. The expected growth is not surprising given a recent report by comScore that shows the number of mobile users is now equal to the number of personal computer (PC/Desktop/laptop) users, and that the rate of mobile user growth is higher than PC users [6] . Though men shop as much as women, when we account for device type, it is known that men shop more on mobile devices than women [7]. However, it is still unknown if perceived risk across device type impacts the number of purchases equally. We theorize that physical asset specificity and temporal asset specificity are inherent for mobile device transactions. We will also show that in terms of transactions costs, mobile users with high perceived risks reduce their order volume the most across all device types. In addition to our theoretical contributions, this study may benefit practitioners in the following ways:

- Esellers may choose to target individuals who have low perceived risk of online transactions.
- Esellers may tailor their advertising campaigns to target PC users, as these individuals are more likely to make online purchases relative to a mobile device.

In the remainder of the paper we first present related work and build our hypotheses in Section 2. We formally present the empirical model used to draw our conclusions in Section 3. We next describe the data, in Section 4, we use in our study and present our results and discuss future research directions in Section 5. We finally conclude the paper in Section 6.

2. Literature and Hypotheses

In this section we discuss other work on the impact of consumers' perceived risk on purchasing behavior, especially in an online setting. Dai et al. [8] presented work in which 2,500 students are asked if shopping intentions change with risks associated with online shopping for each product type, digital (music) and non-digital (apparel). The authors find that perceptions of risk negatively influence purchase intentions. Similarly in a sample of 320 survey participants conducted by Lim [9] an identical result was found, in that increased perceived risk negatively impacts intentions to buy. The results also showed that decreased intentions to buy resulted in fewer purchases in an eShopping mall in Malaysia. A similar result to Lim was found by Miyazaki and Fernandez [10]. The three investigations above are just a small fraction of the studies examining consumer perceived risk in online shopping, [11–17]. The main difference between our work and the aforementioned work is that we consider a survey administered over two separate years, 2009 and 2012, with at least 20,000 participants per year. The sample size represents an order of magnitude more than any other study mentioned so far. Furthermore, unlike the previous work we consider the impact of not only perceived risk but also access device type and its impact on consumers' eCommerce decisions.

2.1. Hypotheses 1 and 2: Perceived Risk and Online Purchasing

In this section we present additional work more closely aligned to our manuscript, on perceived risk and online purchasing, and formally present our first two hypotheses. The most similar paper to ours is that by Narayanan et al. [18] in which the authors use a similar approach, on years 2002 and 2003 of the precursor to the survey we use, to determine consumers' purchase habits. However, they do not consider the type of access device in users' risk attitudes. Conversely, the work of Yan et al. [19] does consider device type, but does not explore the impact of perceived risk on individuals' purchase decisions. As an extension of these studies we put forth the following two hypotheses:

Hypothesis 1) *The probability of making online purchases is independent of an individual's perceived risk for the entire population and for each device type.*

Hypothesis 2) *The number of online orders made is the same for individuals regardless of their perceived risk across all device types.*

We may formally write these hypotheses, $\boldsymbol{H_1}$, for hypothesis 1, and $\boldsymbol{H_2}$, for hypothesis 2 as:

$$\boldsymbol{H_1}\text{: } P\{buy\ online \mid perceived\ risk = high\} == P\{buy\ online \mid perceived\ risk = low\}$$

$$\boldsymbol{H_2}\text{: } \{number\ of\ orders \mid perceived\ risk = high\} =$$

$$= \{number\ of\ orders \mid perceived\ risk = low\}$$

To summarize, the main difference between the work presented here and past work in security and purchase intentions is: in addition to considering the perceived risk for each participant we also consider the access device type, something that, to our knowledge, is not considered in the existing literature.

2.2. Hypothesis 3: Perceived Risk Impact across Device Types

Individuals use mobile phones for multiple purposes. Ono et al. [20] show the different motivations individuals have when browsing on-line vs. physical stores. Similarly, Lu and Su

[21] and Wu and Wang [22] conduct a similar analysis to determine the factors that drive customer intentions to purchase using a mobile device. As we are interested in determining the impact of perceived risk on actual purchase quantity, we do not consider purchase intentions but actual purchases, which as shown by Lim [9] has a positive relationship, but intentions are not equivalent to actual purchases. Chin et al. [23] show that users have a statistically significant lower likelihood of purchasing items online using their mobile device than when using their PC. They also claim that perceived risk is a major factor in preventing individuals from online purchasing. For estimation purposes (and for clarity and ease of comparison), we limit the sub-samples by discrete device types. This leads to our third hypothesis:

Hypothesis 3) *The impact of perceived risk varies across device type.*

Formally we write the third hypothesis:

$$\boldsymbol{H_3}\text{: } For\ the\ regression\ coeffecient\ on\ perceived\ risk\text{: } \beta_{mobile} = \beta_{PC} = \beta_{other} = \beta_{whole\_sample}.$$

2.3. Hypothesis 4: Men with Low Perceived Risk are the Main Drivers of Online Shopping

In another study, Garbarino and Strahilevitz [24] consider the gender gap in online shopping using a self-reported survey. With a sample of 260 individuals, the authors found women were less risk tolerant (more afraid of a 'bad' outcome) than men when purchasing online. The authors also cite related literature indicating that higher perceived risk leads to lower online shopping engagement. In this study, we have both self-reported perceived risk and online purchase volumes of consumers; hence in line with previous findings about male and female risk perceptions we formulate the fourth hypothesis as:

Hypothesis 4,A) *Men that have low perceived risk will be the driving factors behind the number of orders made online.*

To complement similar studies, such as those by Lim, we further postulate an alternative hypothesis:

Hypothesis 4,B) *Individuals that have low perceived risk are the major drivers towards online purchases.*

We formally write the two variants of the hypothesis as:

$\boldsymbol{H_{4,A}}$: $Men\ with\ low\ perceived\ risk\ (=0) are\ the\ primary\ factors\ that\ drive\ online\ shopping.$

$$\boldsymbol{H_{4,B}}: Individuals\ with\ low\ perceived\ risk\ (=0)\ are\ the\ primary\ factors\ that\ drive\ online\ shopping.$$

In the remainder of the manuscript we describe the model and data that we use, and formally test each hypothesis.

3. Hurdle Model

ECommerce behavior can be thought of as two-step process wherein the individual first decides whether to buy online—a binary choice or $\boldsymbol{Y} \in \{0, 1\}$ and then how much to buy $\boldsymbol{Y} \in \{1, 2, 3 \ldots\}$. The variable 'how much to buy' in our model is the number of purchases made (e.g. quantity / intensity of purchasing). Typically in the literature a single equation is used to represent both steps. For instance, as Mullahy [25] showed a Poisson functional form models the joint choice of buying online and how many purchases to make. In the Poisson case, the vector of explanatory variables, called '$\boldsymbol{X}$' is the same for both processes. Another model could be used where the two processes are separate, and thus there could be two different vectors of explanatory variables, called '$\boldsymbol{X_1}$' and '$\boldsymbol{X_2}$'. This is called a 'hurdle model' in the literature.

$\boldsymbol{Let\ X_1 \cup X_2 = X}$ and $\boldsymbol{X_1 \cap X_2}$ need not be empty

For a regular Poisson model we have:

$\mathbf{Pr}(\boldsymbol{Y} = \boldsymbol{i} \mid \boldsymbol{X})$ ~Poisson $\forall_i$ where $\boldsymbol{i = 0, 1, 2, 3, 4} \ldots$ **(1)**

For a two-step hurdle model:

$$\mathbf{Pr}(\boldsymbol{Y} = \mathbf{0} \mid \boldsymbol{X_1}), \mathbf{Pr}(\boldsymbol{Y} \neq \mathbf{0} \mid \boldsymbol{X_1}) \sim \text{Logistic} \quad \textbf{(2)}$$

$$\mathbf{Pr}(\boldsymbol{Y} = \boldsymbol{i} \mid \boldsymbol{X_2}) \sim \text{Geometric for } \forall\, \boldsymbol{i} \geq \mathbf{1} \quad \textbf{(3)}$$

In practical terms the forgoing means the Poisson model limits the researcher to one parametric model; thus we call it the "restricted model". The two-step hurdle procedure uses a logit regression to estimate the probability of buying online and a geometric regression to estimate the number of orders placed. However, one cannot simply say that the hurdle model is 'better' than the Poisson model, it must be tested. A likelihood-ratio (LR) test [26] is used for this purpose (explained below). We are by no means the first to use the two-stage hurdle model. After its introduction by Mullahy, the two-step hurdle model has successfully been used in farm marketing decisions [27], consumer willingness to purchase information good bundles [28], and the impact of employee mobility on firm performance [29].

To test the hypothesis that the restricted (Poisson) model and the general (hurdle) model are indeed different, we use an LR test. The H_0 of the LR-test is that the two models are the same. This test is distributed as Chi-squared with k degrees of freedom (k is the number of independent variables including the intercept). The LR test statistic is below, where LL indicates log-likelihood (subscript λ is for logit, G is for geometric, and P is for Poisson):

$$LR = 2[LL_\lambda + LL_G - LL_P] \quad \textbf{(4)}$$

We further refine the procedure by taking into account the type of device used to access the Internet—PC-only, mobile-only and other-only. Thus we estimate four hurdle models: one for the full sample, and the rest by limiting the sub-sample to those who only use a particular access medium and omit all other users. Each of the sub-sample models is tested against the relevant Poisson model (restricted model).

4. Data

Our data source is the Canadian Internet Use Survey (CIUS), collected by Statistics Canada using a nationally representative household sample from all ten provinces.[1] The 2009 survey has 23,178 observations while the 2012 survey has 22,615 observations. As shown in Table 1, roughly 55 percent of households in both survey years have a female head of the household. In the analysis, when we compare the sex of participants, we are talking about the sex of the head of household. As such, in our analysis we are implicitly assuming that the head of the household does all of the online shopping for the home. We realize that this may not be the case, but as we do not have the sex of the purchaser for each transaction, this is a simplifying assumption that must be made given the available data. The largest age group in the table are those over 55. Most heads of the household have at least some community college education, while only roughly 25 percent have children.

Table 1: Number of observations and expenditures for each household. Note: sex and education are for the head of household

	Year	2009	2012
	No. Households	23,178	22,615

[1] The first wave of the CIUS was conducted in 2005. Afterwards CIUS 2007, 2009, 2010 and 2012 followed. Because the 2005 and 2007 CIUS surveys have low mobile device usage we omit those survey years. Furthermore, in the 2010 CIUS the section entitled 'Group Privacy and Security' does not include the question 'How concerned (are you/would you be) about using your credit card over the Internet?'. In fact, there is no question related to financial security or online banking in the 2010 survey. The 2009 survey in contrast contains the online credit card use question. Thus we could only use the 2009 and 2012 surveys for this research. The response data files were merged to construct a cross-sectional database. A panel file could not be constructed as Statistics Canada does not provide a linkage variable due to their policy of maintaining respondent confidentiality.

Sex	Female	12,817	12,480
	Male	10,361	10,135
Education, highest level attained	High school	5,995	5,887
	Community College	11,104	10,442
	University	6,079	6,286
Children	No	17,539	17,333
	Yes	5,639	5,282
Items	Quantity	74,004	118,021
	Total Expenditure	$ 11,595,307.00	$ 13,240,623.00

Table 2 describes the variables and provides a short description along with the mean and standard deviation for each. The means and standard deviations support the observations we noted in Table 1.

Table 2: Variable description and summary statistics.

Variable	Description	Mean	Std Dev
age	The age of head of household (1:16-24; 2:25-34; 3:35-44; 4:45-54; 5:55-64; 6:65+	3.98	1.62
education	The highest education level of head of household (1:High school or less; 2: Community College/Some post-secondary; 3: University degree)	2.01	0.73
family	Type of household (1:Single family w/ children < 16 yo; 2:Single family w/o children < 16 yo; 3: Single person; 4: Multi-family home	2.11	0.80

income	Household annual income (1:0-$25,000; 2:$25,001-$39,999; 3:$40,000-$63,999; 4:$64,000-$99,999; 5:$100,000+)	2.93	1.41
children	Indicator variable set to 1 if a household has children < 16 yo, 0 otherwise	0.24	0.43
female	Indicator variable set to 1 if head of household is female, 0 otherwise	0.55	0.50
orders	Indicator variable set to 1 if household made online orders, 0 otherwise	0.38	0.49
quantity	The number of online orders made by a household	4.19	13.76

As 64.84% and 58.51% of households did not make any online purchases in 2009 and 2012, respectively, we present the quartiles of non-zero responses for the number of orders (quantity) and total expenditures for each year.

Table 3: Quartile information on quantity and total expenditure.

Value	Year	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Quantity	2009	1	3	5	9.081	10	400
	2012	1	3	6	12.58	12	600
Total Expenditure	2009	$0	$ 200	$ 500	$ 1,423	$ 1,500	$ 60,000
	2012	$0	$ 200	$ 500	$ 1,411	$ 1,200	$ 82,000

The first thing one notices from the distribution on the order quantity and annual expenditure data is that it is a long tailed distribution with most of the mass very close to zero, relative to the maximum value. We also note that some individuals received free goods online, i.e., made purchases but not payments. This may occur with gift cards or coupons. The exact method used to glean free goods/services, was unavailable in both surveys.

Table 4 illustrates the proportion of households that have high perceived risk regarding online security for survey years 2009 and 2012. Question PSQ03 in 2009 (PSQ02 in 2012 survey) of CIUS asks about the use of a credit card for eCommerce: "How concerned (are you/would you be) about using your credit card over the Internet?". In the 2009 survey out of 23,178 households, 11,846 (or 51.1%) were "concerned" or "very concerned" with using a credit card over the Internet. For the 2012 survey, out of 22,615 households 7,412 (or 32.8%) were "concerned" or "very concerned" about using a credit card on the Internet. In our study we code all households that are concerned or very concerned regarding credit card transactions over the Internet as having *high* perceived risk and all others as having *low* perceived risk.

We focus on different modes of eCommerce in terms of the device. The first possible eCommerce device is the PC (laptop or desktop), the second is a mobile phone/tablet/phablet, and the third is a game console (Xbox, PlayStation, Wii). There are of course other combinations of devices: PC & mobile, PC & game, mobile & game, and finally PC & mobile & game, but we do not consider these. The proportion of all groups who pay online with a credit card is 81.7% in 2009 and 87.9% in 2012 given that they make online purchases. The 2012 survey introduced four new payment methods: debit card, PayPal, voucher and rewards card. Of these new methods, 33% of respondents used PayPal and 12.3% used a rewards card. What is not shown in Table 4 is that out of 12,633 households with PC access in 2009, 48.5% have high perceived risk (36.7% in 2012), while 50% (31.2 % in 2012) of those with mobile-only access have high perceived risk, and of those using PC and mobile devices together, 33.7% (23.6% in 2012) have high perceived risk.

Table 4: Access device and perceived risk breakdown.			
Year	Access Device	Low Perceived Risk	High Perceived Risk
2009	None (10,455)	4,782	5,673
	Other-only (18)	7	11
	Mobile-only (72)	36	36
	PC-only (12,633)	6,507	6,126
2012	None (10,318)	8,000	2,318
	Other-only (4,584)	4,254	330
	Mobile-only (301)	207	94
	PC-only (7,412)	4,692	2,720

5. Results

Below we present the results of our analysis in two sections. The first section reports the hurdle model estimates where we compared the restricted model (Poisson) against the two-step hurdle model—for the full sample and for each sub-sample of users. We find in all cases that the hurdle model is preferable to the Poisson model. The results for the four hypotheses are presented in the second section.

5.1. Hurdle model results

The LR test for the full sample Poisson model against the full sample logistic and zero-truncated geometric model is in Table 5, row 3. The sub-sample Poisson and hurdle model LR tests are in rows 4-6 of Table 5. We compute robust standard errors of the estimates with clustering by province. We see that in all cases we can reject the null hypothesis that the Poisson results are the same as the hurdle results. Thus, we proceed in our analysis with only reporting the hurdle model estimates.

Table 5. LR test of restricted model (Poisson) against hurdle model

Model*	Sample or Sub-sample	LR χ^2- test
Poisson_1 vs (logistic_1, ztg_1)	Full	349,409***
Poisson_2 vs (logisitic_2, ztg_2)	PC-only	120,058***
Poisson_3 vs (logistic_3, ztg_3)	Mobile-only	3,329***
Poisson_4 vs (logisitic_4, ztg_4)	Other-only	6,900***
Note that "ztg" denotes zero-truncated geometric and *** denotes statistically significant at $p < 0.01$.		

From Table 6 we see the first-step estimates for the full sample, PC-only users, mobile-only users and other-only users. Sample size ranges from 45,793 (full sample) to 373 (mobile-only). We see that for all users perceived risk has a significant negative effect on the propensity to engage in eCommerce. The highest age category (older than 54) has a significant and negative effect on eCommerce as well. The highest family income quintile (greater than $100,000) has a significant and positive effect on engaging in eCommerce.

Table 6. Hurdle model step 1, logistic regression for engaging in eCommerce (Yes/No)†					
	Description	Full sample	PC-only	Mobile-only	Other-only
		coef/se	coef/se	coef/se	coef/se
high perceived	Indicator	-0.789***	-0.739***	-0.951***	0.480***

risk	variable (IV)=1 if true				
		(0.103)	(0.087)	(0.254)	(0.155)
female	IV=1 if true	0.107*	0.061	0.022	0.434***
		(0.056)	(0.059)	(0.272)	(0.140)
2.edu	IV=1 if community college	0.721***	0.457***	0.138	1.183***
		(0.042)	(0.033)	(0.194)	(0.192)
3.edu	IV=1 if university	1.335***	0.874***	1.356***	2.159***
		(0.049)	(0.059)	(0.344)	(0.247)
2.family	IV=1 if single family w/o children < 16 yo	0.035	0.099***	-0.403	-0.317
		(0.026)	(0.014)	(0.291)	(0.226)
3.family	IV=1 if single person	0.255***	0.520***	-0.113	-0.068
		(0.031)	(0.037)	(0.284)	(0.263)
4.family	IV=1 if multi-family	-0.001	0.166**	0.011	-0.539
		(0.056)	(0.079)	(0.495)	(0.394)
2.age	IV=1 if 25-34 yo	0.358***	0.450***	0.029	-0.750***
		(0.035)	(0.090)	(0.286)	(0.215)
3.age	IV=1 if 35-44 yo	0.113	0.281**	-0.379**	-1.016***
		(0.070)	(0.113)	(0.153)	(0.162)
4.age	IV=1 if 45-54 yo	-0.280***	0.005	-0.064	-2.154***
		(0.096)	(0.132)	(0.404)	(0.208)
5.age	IV=1 if 55-64 yo	-0.558***	-0.152	-0.215	-2.701***
		(0.131)	(0.160)	(0.493)	(0.304)
6.age	IV=1 if 65+ yo	-1.411***	-0.567***	-1.854***	-4.443***
		(0.117)	(0.151)	(0.668)	(0.314)
2.income	IV=1 if \$25,001-\$39,999	0.573***	0.364***	-0.047	0.270
		(0.035)	(0.052)	(0.331)	(0.191)
3.income	IV=1 if	0.982***	0.684***	0.298	0.812***

	$40,000-$63,999				
		(0.058)	(0.074)	(0.337)	(0.141)
4.income	IV=1 if $64,000-$99,999	1.331***	1.009***	0.311	1.067***
		(0.066)	(0.067)	(0.371)	(0.202)
5.income	IV=1 if $100,000+	1.663***	1.321***	0.943***	1.354***
		(0.052)	(0.044)	(0.296)	(0.334)
_cons		-1.672***	-1.420***	-0.698	-2.135***
		(0.077)	(0.085)	(0.429)	(0.243)
Number of observations		45,793	20,045	373	4,602
k		21.000	21.000	21.000	21.000
Log-Likelihood		-24,312.43	-12,282.17	-207.01	-574.02
Adjusted R2		0.202	0.097	0.119	0.341
note: *** p<0.01, ** p<0.05, * p<0.1					
†Cluster robust standard errors (clustered by province)					

Table 7 shows the estimates from the zero-truncated geometric regressions with number of orders as the dependent variable. The functional form of the zero-truncated geometric model is our proxy for the respective demand functions (number of orders placed) for each category of users conditional on price and other factors. For all user-types we see that price is significant and negative (as expected). Perceived risk is significant and negative (as expected) in the number of orders at the 5% level for the entire population, PC, and mobile, but is only significant at the 10% level for other users. High income has a highly significant positive effect on the number of orders placed.

Table 7. Hurdle model step 2, zero truncated geometric estimates for number of online orders†					
	Description	Full sample	PC-only	Mobile-only	Other-only
		coef/se	coef/se	coef/se	coef/se

price	Average value of order	-0.001***	-0.001***	-0.001***	-0.001*
		(0.000)	(0.000)	(0.000)	(0.000)
high perceived risk	Indicator variable (IV)=1 if true	-0.289***	-0.253***	-0.989***	-0.621*
		(0.018)	(0.024)	(0.258)	(0.331)
female	IV=1 if true	-0.166***	-0.208***	0.149	-0.434**
		(0.023)	(0.026)	(0.348)	(0.211)
edu==2	IV=1 if community college	-0.002	-0.055	0.314	-0.073
		(0.056)	(0.052)	(0.297)	(0.147)
edu==3	IV=1 if university	0.220***	0.108	0.324	0.119
		(0.077)	(0.074)	(0.242)	(0.165)
family==2	IV=1 if single family w/o children < 16 yo	-0.088***	-0.190***	0.162	-0.402
		(0.029)	(0.050)	(0.270)	(0.274)
family==3	IV=1 if single person	0.176***	0.133**	0.268	0.301
		(0.040)	(0.062)	(0.237)	(0.233)
family==4	IV=1 if multi-family	0.131	-0.005	0.565	0.462
		(0.092)	(0.140)	(0.450)	(0.856)
age==2	IV=1 if 25-34 yo	0.160***	0.090	-0.473	-0.233
		(0.042)	(0.119)	(0.438)	(0.234)
age==3	IV=1 if 35-44 yo	0.109***	0.057	0.275	-0.253
		(0.039)	(0.126)	(0.431)	(0.313)
age==4	IV=1 if 45-54 yo	-0.078*	0.005	-0.628	-0.440
		(0.047)	(0.117)	(0.516)	(0.313)
age==5	IV=1 if 55-64 yo	-0.110*	0.047	-0.220	-0.527*
		(0.065)	(0.147)	(0.491)	(0.306)
age==6	IV=1 if 65+ yo	-0.253***	-0.076	-0.982	-0.256
		(0.074)	(0.134)	(0.803)	(0.448)
income==2	IV=1 if \$25,001-\$39,999	0.052	-0.071	0.388	0.304**

		(0.121)	(0.119)	(0.365)	(0.134)
income==3	IV=1 if $40,000-$63,999	0.177**	0.062	0.612***	0.841***
		(0.085)	(0.111)	(0.229)	(0.187)
income==4	IV=1 if $64,000-$99,999	0.201***	0.075	0.379	0.978***
		(0.065)	(0.069)	(0.323)	(0.238)
income==5	IV=1 if $100,000+	0.455***	0.338***	1.132***	1.745***
		(0.056)	(0.091)	(0.435)	(0.387)
_cons		1.992***	1.967***	1.729***	1.943***
		(0.117)	(0.176)	(0.399)	(0.253)
Number of observations		17,533	8,322	121	216
k		18.000	18.000	18.000	18.000
Log-Likelihood		-80,215.00	-35,260.39	-554.81	-920.46
Adjusted R2					
note: *** p<0.01, ** p<0.05, * p<0.1					
†Cluster robust standard errors (by province)					

5.2. Hypothesis test results

In this section we present the results of our hypotheses tests. We note that there may be external factors that interact with the likelihood of an individual to conduct eCommerce, such as sex, since women are known to be more cautious than men, see Section 2.3 and Garbarino and Strahilevitz [24] for more elaboration, and wealth--potentially individuals with higher wealth will be less sensitive to having their credit card information misappropriated after an eCommerce transaction. We note that there is indeed correlation between sex, wealth, and perceived risk. However, even if we control for these factors (using interaction terms), the results presented here only change in the thousands, and the statistical significance of what we present in this section remains unchanged. As such, to remove ambiguities, we present results that do not control for such interaction terms.

For H1, we see in Table 8 that the 95% confidence intervals on the estimated coefficient for perceived risk in the full sample, the PC-only sample, and the mobile-only sample clearly do not overlap (by this we mean intersect). This is conclusive evidence to reject the null hypothesis that the propensity to engage in eCommerce is unaffected by the perceived risk. We can see that the predicted mean value of engaging in eCommerce is 0.437 for the whole sample that has low perceived risk; this falls to 0.294 for those who have high perceived risk. The mean value of the probability of engaging in eCommerce for mobile users falls from 0.384 to 0.210 for those that have high perceived risk.

Table 8. Logistic equations for H_1 ($\boldsymbol{H_1}$: $P\{buy\ online \mid perceived\ risk = high\} == P\{buy\ online \mid perceived\ risk = low\}$)

	Margin	z	P>|z|	[95% Conf.	Interval]
	Full Sample				
perceived risk=0	0.437	30.48	0.000	0.409	0.465
perceived risk=1	0.294	33.31	0.000	0.277	0.311
	PC-only				
perceived risk=0	0.485	29.69	0.000	0.453	0.517
perceived risk=1	0.326	42.20	0.000	0.311	0.341
	Mobile-only				
perceived risk=0	0.384	17.38	0.000	0.340	0.427
perceived risk=1	0.210	5.96	0.000	0.141	0.279
	Other-only				
perceived risk=0	0.044	8.63	0.000	0.034	0.054
perceived risk=1	0.062	8.71	0.000	0.048	0.076

Hypothesis 2 states that the demand for orders (quantity of orders) is the same across individuals with high perceived risk and low perceived risk. We test the hypothesis first with the whole sample and then test it on each sub-sample: PC-only users, mobile-only users and other-only users. We can see from Table 9 that the 95% confidence intervals on the number of orders made by device type for each population, low perceived risk individuals and high perceived risk individuals, for the whole sample, PC-only and mobile-only do not overlap. For example, when considering the whole sample, the 95% confidence interval on the number of orders made for individuals with low perceived risk is [2.058, 2.230] and for individuals with high perceived risk is [1.746. 1.929]. As the two intervals do not overlap, i.e., 1.929 < 2.058, we reject H2 for the whole sample, an analogous analysis holds for all other subsamples. Thus we reject H2. For mobile-only users that have low perceived risk we see that their mean number of orders is 2.361 which is greater than all other users. However, if mobile users have low perceived risk their mean number of orders falls to 1.165 which is the lowest value in the table. It is interesting to note that if we compare the 95% confidence intervals across device types for a fixed perceived risk, we note that mobile-only users with low perceived risk purchase more than PC-only users with low perceived risk. However, this relationship is reversed when considering PC-only users with high perceived risk who purchase more than mobile-only users with high perceived risk.

Table 9. Zero-truncated geometric model margins for full and sub-samples ($\boldsymbol{H_2}$: $\{number\ of\ orders \mid perceived\ risk = \ high\} == \{number\ of\ orders \mid perceived\ risk = low\}$)

Full Sample (N=17,533)	Margin	z	P>|z|	[95% Conf. Interval]

perceived risk = 0	2.144	48.76	0.000	2.058	2.230
perceived risk = 1	1.838	39.41	0.000	1.746	1.929
PC-only (N=8,322)					
perceived risk = 0	1.856	32.70	0.000	1.745	1.968
perceived risk = 1	1.600	33.71	0.000	1.507	1.693
Mobile-only (N=121)					
perceived risk = 0	2.361	22.07	0.000	2.151	2.570
perceived risk = 1	1.165	8.21	0.000	0.887	1.444
Other-only (N=216)					
perceived risk = 0	1.952	19.14	0.000	1.752	2.151
perceived risk = 1	1.314	4.25	0.000	0.708	1.920

Hypothesis 3 states that the coefficient on perceived risk should be the same across every access device type. We compute a Wald test (following a χ^2 distribution) and show the results in Table 10. We reject the hypothesis for: the full sample and mobile users, PC and mobile users (and for full-pc-mobile, and full-pc-mobile-other). However, we cannot reject the hypothesis for: the full sample and PC users, for the full sample and other users, for PC and other users, and for mobile and other users. The most important finding is that mobile users differ from PC users and from the full sample.

Table 10. Effect of perceived risk on order quantity from zero-truncated geometric regressions ($\boldsymbol{H_3}$: $For\ the\ coeffecient\ on\ perceived\ risk$: $\beta_{mobile} = \beta_{PC} = \beta_{other} = \beta_{whole\_sample}$.)

Test for $\beta_1 = \beta_2$	χ^2	Prob> χ^2
$\beta_{full} = \beta_{pc}$	2.36	0.1247
$\beta_{full} = \beta_{mobile}$ †	12.12	0.0005
$\beta_{full} = \beta_{other}$	2.77	0.0959
$\beta_{pc} = \beta_{mobile}$ ‡	13.12	0.0003
$\beta_{pc} = \beta_{other}$	3.45	0.0632
$\beta_{mobile} = \beta_{other}$	2.45	0.1177
$\beta_{full} = \beta_{pc} = \beta_{mobile}$	13.99	0.0009
$\beta_{full} = \beta_{pc} = \beta_{mobile} = \beta_{other}$	16.57	0.0009

Full sample N=17,533; PC-only sample N=8,322; mobile-only sample N=121; other-only sample N=216

Note that for full sample, zero-truncated geometric only uses quantity of orders greater than zero.

†Coefficient on β_{full} = -0.289 and coefficient on β_{mobile} = -0.989

‡ Coefficient on β_{pc} = -0.253 and coefficient on β_{mobile} = -0.989

Hypothesis 4A states that men with low perceived risk are the heaviest eCommerce users. We test for this hypothesis by examining the margins of each category, male and female, on the number of purchases made. What the margins measure is the additional number of orders one expects to receive if an individual matching these attributes were added to the population, for example, the first row of Table 11 states that a man with low perceived risk will on average make 2.231 additional purchases.

We find no support for hypothesis 4A in our analysis, since with all access types the 95% confidence interval overlaps, with women that have low perceived risk, though only slightly as seen in Table 11. In particular, the 95% confidence interval on the margin for men with low perceived risk is [2.151, 2.310] and for women with low perceived risk the 95% confidence interval is [1.973, 2.167]. As these intervals overlay, 2.151 < 2.167, we cannot say with 95% confidence that these two margins are different. As such, we cannot support H4A for the entire sample. For all other categories, men that have low perceived risk tend to drive more online sales at the 5% level.

Table 11. H4A: Men with perceived risk = 0 are the primary factors that drive online shopping
($\boldsymbol{H_{4,A}}$: $Men\ with\ low\ perceived\ risk = 0\ are\ the\ primary\ factors\ that\ drive\ online\ shopping$.)

Zero-truncated geometric equations, margin for perceived risk and female

Perceived Risk	Female	Margin	z	P>|z|	[95% Conf. Interval]	
			Full Sample			
Low	No	2.231	55.00	0.000	2.151	2.310
Low	Yes	2.070	41.72	0.000	1.973	2.167
High	No	1.924	44.60	0.000	1.840	2.009
High	Yes	1.763	33.79	0.000	1.661	1.866
			PC-only			
Low	No	1.971	34.19	0.000	1.858	2.084
Low	Yes	1.765	29.79	0.000	1.649	1.881
High	No	1.715	37.43	0.000	1.625	1.804

High	Yes	1.509	28.81	0.000	1.406	1.611
			Mobile-only			
Low	No	2.307	14.70	0.000	1.999	2.614
Low	Yes	2.406	11.86	0.000	2.008	2.804
High	No	1.111	4.47	0.000	0.624	1.598
High	Yes	1.210	7.48	0.000	0.893	1.527
			Other-only			
Low	No	2.220	10.55	0.000	1.808	2.633
Low	Yes	1.763	18.75	0.000	1.579	1.948
High	No	1.583	4.63	0.000	0.912	2.253
High	Yes	1.126	3.51	0.000	0.497	1.755

The overlap between women and men that have low perceived risk suggests that their marginal number of orders should be greater than individuals that have high perceived risk. As seen in Table 12, we note that indeed those who have low perceived risk generate more orders across all devices types except for "other". However, this may be an artifact of the low number of observations for this device category.

Table 12. H4B: Individuals with perceived risk = 0 are the primary factors that drive online shopping
($\boldsymbol{H_{4,B}}$: $Individuals\ with\ low\ perceived\ risk =$
$0\ are\ the\ primary\ factors\ that\ drive\ online\ shopping$.)

perceived risk	Margin	Std. Err.	Z	P>|z|	[95% Conf. Interval]	
			Full Sample			
Low	2.144	0.044	48.76	0.000	2.058	2.230

High	1.838	0.047	39.41	0.000	1.746	1.929
PC-only						
Low	1.856	0.057	32.70	0.000	1.745	1.968
High	1.600	0.047	33.71	0.000	1.507	1.693
			Mobile-only			
Low	2.361	0.107	22.07	0.000	2.151	2.570
High	1.165	0.142	8.21	0.000	0.887	1.444
Other-only						
Low	1.952	0.102	19.14	0.000	1.752	2.151
High	1.314	0.309	4.25	0.000	0.708	1.920

5.3. Implications for Theory

In this section we will attempt to convey to the reader how the results fit with transactions cost theory [30, 31]. The transaction cost approach maintains that institutions have the main purpose and effect of economizing on transaction costs. Transaction cost analysis supplants the usual preoccupation with technology and steady-state production costs with an examination of the comparative costs of planning, adapting, and monitoring task completion under alternative governance structures. Transaction cost economics assumes that agents are subject to bounded rationality. In other words, their behavior is intendedly rational but only limitedly so, and they are given to opportunism (moral hazard). The primary function of transactions cost economics is to organize transactions so as to economize on bounded rationality while simultaneously safeguarding them against the hazards of opportunism.

Three primary factors are responsible for the differences amongst transactions: (1) asset specificity--transactions that are supported by investments in durable transaction-specific assets experience ‘lock-in’ effects and *ex post* contracting arrangements may be either not possible or troublesome. There are five types of asset specificity: site, physical, human, dedicated and temporal. (2) uncertainty--governance structures differ in their ability to respond to disturbances--this would vanish if not for bounded rationality since a detailed strategy for every kind of problem could be drawn up in advance otherwise. (3) frequency--does the volume of transactions processed through a specialized governance structure justify its existence? Specialized governance structures are better suited to the needs of nonstandard transactions than unspecialized structures. For example, one-shot transactions are susceptible to moral hazard and thus safeguards (such as insurance, and/or alternatives to market governance) should be in place to protect both parties. On the other hand, frequent transactions (a repeated game) between contracting parties builds trust and familiarity, and thus limits opportunistic behavior; thus the market may be an efficient governance mechanism in this case.

In our context, we have a trilateral relationship with consumers, credit card companies and eSellers. Each credit card company and eSeller has their own terms of agreement for delivery of the product or service. The consumer can choose from multiple eSellers and also can choose from multiple credit card companies. Because there are multiple eSellers and credit cards with specific terms of agreement, the consumer who is boundedly rational should consider the worst case strategy: that the credit card company and the eSeller will act in the least favorable way towards them. As such, they may choose not to engage in eCommerce. Whether the consumer engages in eCommerce or mobile commerce is immaterial since both types of transaction are inherently uncertain and require human asset specificity (the ability to use the website of the eSeller, e.g. 'one click' orders from Amazon). In our case, the market is the governance mechanism. Therefore uncertainty and frequency play an important role in eCommerce. Consumers who are more familiar with particular eSellers will feel less threatened.

In terms of m-commerce, a mobile device may require a specific app, which means that there is physical asset specificity. Furthermore, there is often an urgency to m-commerce, in that many consumers wish to buy 'in the moment' (i.e. theater tickets). This unique aspect of m-commerce lends itself to temporal asset specificity. The table below summarizes our assertions.

Table 13. Transactions costs and eCommerce

	PC	Mobile
Asset specificity		
• Site specificity: co-location of assets involved in a transaction		
• Physical specificity: co-dependencies of the asset; i.e. eCommerce may require an app to		x

be downloaded in order to function		
• Human specificity: knowledge of website and 'one-click' buying can be tied to one specific eSeller (i.e. Amazon)	x	x
• Dedicated specificity: a physical investment tied to a specific eSeller		
• Temporal specificity: a time dependent asset that is important to the user		x
Uncertainty	x	x
Transaction frequency	x	x

If we consider our findings, in 2012 perceived risk for PC users was 36.7%, for mobile it was 31.2% and for PC & mobile it was 23.6%. On the surface perceived risk has the greatest effect on both PC and mobile users, however the largest impact is on mobile users. Here we will discuss each hypothesis test in turn. Hypothesis one is about the probability of engaging in eCommerce versus not engaging in eCommerce and we find that PC users have higher perceived risk than mobile users. Our contention is that temporal asset specificity is very important to mobile users. For hypothesis two, the number of orders based on perceived risk, we find that a smaller proportion of mobile-users have high perceived risk. But if they are risk averse, then they drastically curtail the number of orders. In terms of hypothesis three, the coefficient on perceived risk is different across device types. This is indicative of human asset specificity because sellers may have their own mobile application (each requiring time to learn) as opposed to PC users who may have a single common web interface that they are accustomed to using. For hypothesis four part (b) we find that individuals with low perceived risk order more than others across all device types. In particular for eCommerce order volume, for the full sample we see a 14.27% difference between low and high perceived risk, for PC users we see a 13.79% difference between low and high perceived risk, for mobile users we see a 50.66% difference between low and high perceived risk, and for other-users we see a 32.68% difference between low and high perceived risk. Thus, mobile users who have low perceived risk buy significantly more than their high perceived risk counterparts. This is because of uncertainty, which is linked to perceived risk.

5.4. Implications to Practice

Our study may benefit practitioners by informing marketing strategies. For example we show that consumers with risk tolerance transact more, and thus it would be beneficial to target these individuals. Furthermore, to allay the fears of low risk tolerance mobile users, marketing strategies could stress the invulnerability of proprietary apps and the strength of encryption algorithms to protect the mobile user. Alternatively, managers could simply direct their advertising campaigns at PC users (they have a higher probability of engaging in eCommerce, but have higher perceived risk of online transactions), or they could try to convince PC users that mobile transactions are just as safe as traditional online transactions. This could have an added benefit of increasing sales through the use of two devices instead of one.

5.5. Limitations and Future Research

Our results may be useful to practitioners as well as academics considering eCommerce issues. However, the study has its limitations. For areas of future work, one may try to address these limitations. In the remainder of this section, we discuss some limitations and explain why addressing these limitations in the future may be fruitful.

In the data we only know the sex of the head of the household that participated in the survey. We do not know the makeup of the household, nor do we know who in the household actually made the purchases and used the devices. As such, in future studies, it may be interesting to see if there are household effects on individuals' purchasing habits. In addition, it is unknown what aspects of mobile devices make an individual less likely to participate in eCommerce: there may be physical limitations such as screen size or tactile feedback that preclude individuals from engaging in eCommerce with their mobile devices. Disentangling these physical limitations from perceived risk will inform practitioners on the impact of both of these factors on mobile eCommerce. Further, the purchase data presented was entirely self-reported. This means that there may be willful or accidental omissions in the purchase data. Though this is not something we can address in the current study, in the future having anonymously logged personal shopping data available may curtail such omissions. Similarly, merging self-reported or logged user data with vendor shopping log data will truly complete the picture.

Currently, due to the self-reported nature of the study, it is unclear if a participant uses a mobile device for purchasing or just browsing. Vendor and user logged data will be able to disambiguate this issue, and will empower eSellers and researchers to make a finer distinction between mobile and PC eCommerce. Finally, following the idea of vendor data, we are currently unable to determine other factors that may lead to different purchasing behavior. We showed that consumers, regardless of their perceived risk, are more likely to make purchases using a PC than their mobile device. However, it is unclear if this is due to natural design limitations associated with a mobile device, e.g., smaller screens, smaller buttons, difficulty to enter information, etc. An eSeller may actually experiment with different mobile designs to see if they actually lead to different purchasing decisions, regardless of perceived risk.

6. Conclusion

Our objective was to investigate whether an individual's perceived risk affects eCommerce when we account for access device type. Before we directly answered the question, we tested for the suitability of a hurdle estimation model versus a more restrictive form of a Poisson model. We found in all cases the hurdle model was preferable to the Poisson model. Our hypothesis test results are summarized next. For Hypothesis 1, we found that perceived risk is important for eCommerce, both for mobile users as well as traditional PC users. The probability of buying online was greater for PC users than mobile users for both categories of consumer—low and high perceived risk. The more interesting phenomenon is that high perceived risk mobile users' marginal probability is 0.210 for perceived risk, while for PC users it is 0.326, which is significantly greater. We also find that the number of orders for PC-based and mobile-based eCommerce differ significantly for consumers with high versus low perceived risk. The 95% confidence intervals for the marginal effect of perceived risk $\{0, 1\}$ on the number of purchases do not overlap (intersect) for mobile users nor for PC users.

Interestingly, the margins for PC users are 1.6 for low and 1.856 (16% larger) for high perceived risk consumers; while for mobile users the high perceived risk marginal effect is 1.165 and for low perceived risk it is 2.361 (103% larger). Thus for mobile users who have low perceived risk, they buy significantly more than their high perceived risk counterparts. We also ascertain whether the coefficient on the effects of perceived risk on the number of orders is the same for every device type. We find for the full sample and mobile devices that the coefficients are statistically different (at 0.1% level), and for PC and mobile they are statistically different (at 0.1% level).

We do not find support for our assertion that men with low perceived risk drive eCommerce. Instead, we find support for our secondary assertion that individuals with low perceived risk drive eCommerce regardless of device type. For the full sample, the PC-only sub-sample and the mobile-only sub-sample we find support for the assertion since none of the 95% confidence intervals for the estimated coefficients overlap. Mobile users who have low perceived risk have the greatest propensity to order online (although the sample size is relatively small). With our qualifier for sample size in mind, it may be useful for eSellers to test whether targeting mobile users for mobile commerce yields any benefits to the bottom line.

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