THE ROLE OF RISK IN E-RETAILERS' ADOPTION OF PAYMENT METHODS: EVIDENCE FOR TRANSITION ECONOMIES

Leo VAN HOVE
Department of Applied Economics (APEC)
Vrije Universiteit Brussel
Room C.2.29, Pleinlaan 2, B-1050 Brussels, Belgium
E-mail: Leo.Van.Hove@vub.ac.be
Tel.: +32 2 629.21.25

Farhod P. KARIMOV[1]
Department of Business
Westminster International University in Tashkent
Room 2.17, Istiqbol str. 12, Tashkent 100047, Uzbekistan
E-mail: Farhod.Karimov@gmail.com
Tel.: +998 71 2387411

[1] Corresponding author.

THE ROLE OF RISK IN E-RETAILERS' ADOPTION OF PAYMENT METHODS: EVIDENCE FOR TRANSITION ECONOMIES

Abstract

We use logit analysis to exploit a self-collected dataset on the payment and delivery options offered by the vast majority of B2C websites in 5 Central Asian transition economies. Specifically, we conduct a supply-side test of the Transaction Context Model, which highlights the role of perceived risk. Our results confirm that higher product risk increases the probability that e-retailers adopt lower-risk, 'pay now' instruments (such as debit cards). Moreover, merchants who offer higher-risk delivery options are also more prone to adopt higher-risk payment instruments (such as credit cards). Our control variables also yield interesting results. Pure-plays are more likely to adopt online payment methods and less likely to adopt offline alternatives. Sites that target international markets are also more likely to adopt online payment methods, but do not shun (local) offline substitutes. Finally, we find evidence that the offline penetration of a payment instrument positively affects online merchant adoption. (149 words)

Keywords: online payment methods, transaction context, risk, delivery methods, B2C e-commerce, transition economies

THE ROLE OF RISK IN E-RETAILERS' ADOPTION OF PAYMENT METHODS: EVIDENCE FOR TRANSITION ECONOMIES

Abstract

We use logit analysis to exploit a self-collected dataset on the payment and delivery options offered by the vast majority of B2C websites in 5 Central Asian transition economies. Specifically, we conduct a supply-side test of the Transaction Context Model, which highlights the role of perceived risk. Our results confirm that higher product risk increases the probability that e-retailers adopt lower-risk, 'pay now' instruments (such as debit cards). Moreover, merchants who offer higher-risk delivery options are also more prone to adopt higher-risk payment instruments (such as credit cards). Our control variables also yield interesting results. Pure-plays are more likely to adopt online payment methods and less likely to adopt offline alternatives. Sites that target international markets are also more likely to adopt online payment methods, but do not shun (local) offline substitutes. Finally, we find evidence that the offline penetration of a payment instrument positively affects online merchant adoption. (149 words)

Keywords: online payment methods, transaction context, risk, delivery methods, B2C e-commerce, transition economies

1. Introduction

E-commerce depends greatly on the availability of secure payment channels and a reliable delivery infrastructure (Gavish and Tucci, 2006; Ramanathan, 2010). Both are important drivers of e-commerce adoption. On the supply side, any e-commerce business must, by definition, provide at least one type of payment and delivery mechanism (Hawk, 2004). On the demand side, the availability of convenient payment and delivery options may affect consumers' decision to purchase from a website or not (Alzola and Robaina, 2010).

The majority of prior studies have focused on the impact of payment (and delivery) options on *consumer* uptake of e-commerce (e.g., Koyuncu and Bhattacharya, 2004; Mascha et al., 2011); the supply side has largely been ignored. In this paper, we therefore focus on the latter. In terms of geographical focus, we have been guided by two related observations. First, poor online payment facilities and erratic logistics are the most widely cited problems of engaging in business-to-consumer (B2C) e-commerce in developing countries in general (Molla and Licker, 2005; Odedra-Straub, 2003). Second, while several scholars have acknowledged the importance of research on Information and Communication Technologies (ICT) specifically focused on transition economies[i] - see, for example, Roztocki and Weistroffer (2009) - empirical evidence on the diffusion of e-commerce in these countries is in short supply.

In view of these considerations, we decided to examine the adoption of payment methods by B2C e-retailers in Central Asia, and more specifically in Kazakhstan (Kz), Kyrgyzstan (Kg), Tajikistan (Tj), Turkmenistan (Tm), and Uzbekistan (Uz), as these are the biggest markets in the region - albeit, and this is interesting in itself, at different levels of economic advancement. Since little or no prior information was available, we decided to collect primary data ourselves. This has resulted in a unique database comprising information on 194 B2C e-commerce websites, which should come close to covering the entire population in the five countries that we study (at least at the time of collection of the data). As we will document in Section 4, our Central Asian e-retailers accept a markedly different mix of payment instruments compared to their counterparts in developed countries. In our dataset, adoption also varies dramatically, not only between but also within countries. This makes our sample ideally suited for our purposes; testing our main hypotheses would in fact seem just about impossible for countries where, say, the vast majority of websites accept credit cards.

In what follows, we use logit analysis to explain the adoption of selected payment methods by Central Asian e-retailers – for example, whether they accept credit cards or not - by means of site-, sector- and country-level variables. The focus of our analysis is on the role of product and delivery risk, in a test of the theoretical framework proffered by Liezenberg et al. (2007). Our results confirm that higher product risk increases the probability that online merchants adopt lower-risk, 'pay now' instruments (such as debit cards). Also in line with the transaction context model, we find a negative relationship between product risk and the adoption of credit cards, which are 'pay later' and therefore higher-risk for the seller. However, here we cannot exclude a competing explanation (in the form of higher transaction fees). Interestingly, we also find that product and delivery risk are interlinked, in that merchants who offer higher-risk delivery options are also more prone to adopt higher-risk payment instruments. To be clear: we do not attempt to explain the adoption of delivery methods as such. We only discuss delivery methods so as to be able to analyze their symbiotic relationship with the payment methods offered by a site.

The remainder of the paper is structured as follows. In the next section, we define the major payment and delivery methods that are relevant for our research and we document the current state of affairs in Central Asia. In Section 3 we introduce the theoretical framework and develop our hypotheses. In Section 4 we explain the data collection, define the variables, provide descriptive statistics, and set out our methodology. Finally, Section 5 presents our results and Section 6 concludes.

2. The context: offline adoption and usage of payment instruments in Central Asia

In this Section, we first introduce a simple classification of the payment instruments that are most relevant for our research. We then use the classification to describe which of these instruments exist in the countries that we study, and – to the extent that data are available – discuss how popular they are 'offline'; that is, in the physical world. We do this in order to set the scene for our empirical analysis in Section 5, and especially because we also intend to test whether the offline popularity of a payment instrument among consumers positively impacts its adoption by e-retailers.

Table 1. Classification of payment instruments

		time of payment		
		Pay before	**Pay now**	**Pay later**
medium	**Electronic**	- online voucher - electronic wallet - gift card, prepaid card, electronic purse	- debit card - payroll card - electronic giro or online bank transfer	- credit card - charge card
	Paper	- money order - paper voucher	- cash-on-delivery (COD) - pay at post office - bank transfer	- cheque - paper invoice

Source: Authors' own compilation based on FFIEC (2010) and prior literature such as Bleyen at al. (2009); Polasik and Fiszeder (2010); Stroborn et al., (2004); and Van Bossuyt and Van Hove (2007).

Table 1 identifies six major types of payment instruments by combining two dimensions, namely *medium* and *time of payment*. The first dimension is self-explanatory, and distinguishes more 'traditional' from more innovative instruments. By doing so, it by and large also sets apart instruments that by their very nature are less efficient or even ill-suited for use in e-commerce from instruments that either have been adapted to the Internet environment (such as credit cards and online bank transfers) or that have been specifically developed for the online world (electronic wallets). The second dimension refers to the moment in time at which the settlement of the payment takes place and this from the payer's perspective. In this regard, *pay before* refers to payment instruments that require the payer to possess prepaid monetary value prior to the purchase of goods or services (FFIEC, 2010).

Holders of electronic purses (also called stored-value cards), for example, first need to charge their card by depositing funds into an account that is held by the issuer. *Pay now* refers to payments that are settled (almost) immediately. This category comprises cash-based transactions (which have immediate finality) and payments by means of debit cards (where the current account of the payer is debited immediately if the system works in real-time, or with a slight delay otherwise). Conversely, *pay later* instruments allow the payer to postpone settlement until the end of the month (with so-called delayed debit cards – which, importantly, are typically classified under credit cards) or even longer (with 'real' credit cards).

In the traditional socialist system, households could only use cash, and all money transfers among enterprises were handled by the central bank (Fries and Taci, 2005). In today's Central Asia, the range of payment instruments that can be used for offline, real-world transactions is obviously larger than in the past. However, in terms of usage, traditional paper-based instruments such as cash continue to dominate, and in most countries *pay later* instruments such as credit cards are not yet common. Also, despite the fact that two decades have passed since the collapse of the Soviet Union, in many transition countries the financial sector is still not mature enough to handle, for example, online bank transfers (ICT Policy Project, 2008). In Table 2, we have attempted to document the current state of the (non-cash) payments market in the five countries under investigation. Unfortunately, even though we have used a wide range of sources, the picture is patchy and not always fully consistent. Still, Table 2 does highlight a number of interesting inter-country differences.

A first observation relates to the wide divergences in the relative importance of the 'unbanked'; that is, adults who have no access to formal financial services. According to World Bank data relating to 2011, 42% of the adult population in Kazakhstan would have an account at a formal financial institution, whereas this figure is just about 0% in Turkmenistan. EBRD survey data that look at the % of households (instead of individuals) that have a *bank* account are predictably lower, but the discrepancies remain. Note that the correlation between the two indicators is high (0.92), but not perfect. Especially the 1.7% for Uzbekistan in the EBRD data catches the eye.

Table 2. State of the payment cards market: inter-country comparison

	Kazakhstan	Kyrgyzstan	Tajikistan	Turkmenistan	Uzbekistan
General information					
Population (in 2009) [e]	15 888 000	5 321 000	6 952 000	5 110 000	27 767 000
GDP per capita, in US $ (in 2009) [e]	6 870	860	716	3 904	1 182
Financial inclusion					
Bank account (% households, in 2010) [f]	10.4%	0.5%	0.7%	n.a.	1.7%
Account at a formal financial institution (% age 15+, in 2011) [g]	42%	4%	3%	0%	23%
Penetration of payment cards					
Number of cards issued (mid-2010)	8 048 700	184 929	69 050	n.a.	7 000 000
Local brands	167 900	109 393	-	-	-
International brands	7 880 700	75 536	-	-	100 000 [b]
Visa	6 504 900	74 591	-	-	-
MasterCard	-	945	-	-	-
Europay	1 367 300	-		-	-
Number of cards issued per 1,000 people	507	35	10	n.a.	252
Usage of payment cards					
Volume of transactions (estimate for 2010, except Uz: 2007)	139 200 000	3 331 608	1 306 800	-	(14 500 000) [c]
Value of transactions, in US $ (estimate for 2010) [a]	22 136 278 668	257 005 900	142 879 968	-	3 325 123 152 [d]
Average value of transaction, in US $ (estimate for 2010, except Uz)	159	78	109	-	(229)
Survey data on card adoption					
Credit card (% households, in 2010) [f]	5.9%	0.7%	1%	n.a.	0.8%
Credit card (% age 15+, in 2011) [g]	9%	1%	1%	0%	3%
Debit card (% households, in 2010) [f]	7.3%	0.2%	0.1%	n.a.	4.3%
Debit card (% age 15+, in 2011) [g]	31%	2%	2%	0%	20%

Note: numbers do not always add up due to rounding. Also, because data sometimes relate to different years, some of the indicators should be seen as estimates, and comparability across countries can be imperfect. For example, most usage figures for Uz relate to 2007 (which is why they appear between brackets). Note also that, with the exception of Uz, the figures on the number of transactions were extrapolated based on monthly, quarterly or half-yearly figures. [a] Values converted into U.S. dollars ($) at the official exchange rate set by the respective central banks (as of August 25, 2010): USD 1 = KZT 147.12; USD 1 = KGS 46.52; USD 1 = TJS 4.38; USD 1 = TMM 2.85; USD 1 = UZS 1,624.
Sources: Authors' own compilation based on National Bank of the Republic of Kazakhstan (2010); National Bank of the Kyrgyz Republic (2010); National Bank of Tajikistan (2010); National Bank for Foreign Economic Activity of the Republic of Uzbekistan (2010); [b] Plus Journal (2010) ; [c] Avesta Investment Group (2008), MoneyNews (2007); [d] Trend Capital (2010); [e] World Bank (2010); [f] EBRD (2011); [g] Demirguc-Kunt and Klapper (2012).

When it comes to payment cards, we have used two types of sources. For one, we have used (mainly) central bank publications to compile hard data on the number of cards issued and on the volume and value of transactions. However, these data only make a distinction, if at all, between international and local card brands. Crucially, 'international brands' need not equate with ‘credit cards’; Visa Electron and Maestro, for example, are debit card brands. We have therefore complemented the hard data with survey data from the World Bank and the EBRD.

Starting with the hard data, it can be seen that, compared to its neighboring states, the adoption of cards from international schemes is well advanced in Kazakhstan (with a penetration rate of roughly 50% in 2010). A limited number of such cards also circulate in Kyrgyzstan and Uzbekistan. Tajikistan and Turkmenistan are missing observations. Interestingly, in Uzbekistan local cards dominate the market. Indeed, the bulk of the 7 million cards mentioned are local debit cards (of a specific type). Of the roughly 6 million cards that the Bank of Uzbekistan, for example, had issued by the end of 2008, 98% were local cards (Plus Journal, 2010). Importantly, the majority of the debit cards issued by Uzbek banks can only be used to pay at Point-of-Sale (POS) terminals (either fixed or mobile), and cannot be used online. We will refer to these cards as “payroll cards” as they are often marketed to employers as a cost-effective means of providing wages to employees who lack a traditional banking relationship (FFIEC, 2010). Continuing our overview, both Kyrgyzstan and Tajikistan are clearly lagging behind, with (overall) penetration rates of merely 3.5% and 1%, respectively. Turkmenistan is again a blank spot.

Confronting these numbers with the survey data on card adoption reveals that the bulk of the international cards issued in Kazakhstan are in fact not credit but debit cards. According to the World Bank data, 31% of the Kazakhs would have a debit card and 9% a credit card. Taking into account that certain individuals may well have multiple cards, these figures tally relatively well with the 50% penetration rate of international cards mentioned above. The EBRD data are lower because they are measured on the level of households, but they are consistent with the World Bank data. For credit cards the correlation between the EBRD and World Bank data is 0.96; for debit cards it is even 0.99.

Even though Table 2 paints only a partial picture of the offline payments market in Central Asia, it does demonstrate that e-commerce ventures in these countries face additional challenges compared to their counterparts in the developed world. Indeed, local e-retailers are handicapped by the low (credit) card penetration and also by the complete absence of an online banking system. As we will document in 4.2, Central Asian e-retailers have responded to the problem (1) by accepting, more so than their western counterparts, payment instruments that we have deemed ‘traditional’ when discussing Table 1 (COD, paper bank transfers, etc.), and (2) by resorting to delivery methods that fit these payment options. (More on this symbiotic relationship between payment and delivery methods in 3.1.)

3. Theoretical framework and hypotheses

In this section we first summarize the 'transaction context model' developed by Liezenberg et al. (2007), which claims that risk is the key driver of (online) payment behavior. We rely on this model to underpin our core hypotheses. In subsection 3.2, we discuss other potential determinants of the adoption of online payment methods by e-retailers – factors that we try to control for in our regressions.

3.1. The role of risk in (online) payment behavior

In a 2007 article in a payments journal, Liezenberg et al. (2007) claim that risk is the key determinant of the transactional behavior of both buyers and sellers. Liezenberg et al. underpin this claim by developing the so-called 'transaction context model' (TCM), which highlights the factors that influence the risk perceived in a transaction. They also apply their framework to a number of practical examples. Li et al. (2003) also present a theoretical framework that models the choice of the payment method as a function of, among other factors, the risk involved for the parties to the transaction. Compared to the Li et al. model, the Liezenberg et al. model is less formal but more realistic. Indeed, Li et al. seem to suggest that, irrespective of the payment instrument used, buyer and seller *both* face a fraud risk – which need not be the case, as will be demonstrated below.[ii] In what follows we therefore rely on Liezenberg et al.'s TCM.

The starting point of the TCM is the observation that a transaction typically consists of two actors (buyer and seller) and three core processes: agreement (A), payment (P), and delivery (D) (o.c., p. 219). Each of these processes contains a (perceived) level of risk that is distributed between buyer and seller: R_A is the risk that an agreement is not clear or cancelled, R_P is the risk that the payment is not executed or not guaranteed, and R_D is the risk that the delivery does not take place (Innopay, 2009, p. 70). The total risk perceived in a transaction, R, is thus given by $R = f(R_A, R_P, R_D)$. Liezenberg et al. also point out that, one level lower, at each step in the transaction, the risk perceived by either actor is influenced by the 'transaction context', which is defined as "the total of situational circumstances" (2007, p. 220). Liezenberg et al. distinguish four factors that constitute the transaction context: (i) the timeline (t) and order in which the processes are executed; (ii) the location (l) - physical or virtual; (iii) the relation (r) between buyer and seller - anonymous, known, or trusted[iii] ; and (iv) the characteristics of the product (p) that is exchanged. In symbols: $R_X = f(r_t, r_l, r_r, r_p)$; where X can be A, P, or D.[iv]

Concerning r_l (the risk associated with the location of a transaction process) and r_r (the risk associated with the relation between buyer and seller), Liezenberg et al. point out, respectively, that virtual and/or distanced locations of the actors typically increase perceived risk, and that repetitive transactions typically entail a higher degree of trust than do incidental transactions. Given that the present paper only examines the online environment and given that in adopting an online payment method e-retailers always have to factor in that it can be used by a new, unknown customer, neither r_l nor r_r appear relevant for our research.[v] However, the two other factors clearly are.

Concerning r_t (the risk associated with the timing of a transaction), it is important to realize that in a traditional face-to-face retail setting, A, P and D are completed at the same time, in one place (A = P = D). As a result, the risk is shared equally between buyer and seller. However, Liezenberg et al. stress that with the introduction of distance selling (first mail order, then telephone order and now e-commerce), A, P and D "are disconnected in time and place, allowing for changes in the order of the processes and resulting in unbalanced risks for the buyers and sellers involved" (o.c., p. 220). That is, while a transaction always needs to start with an Agreement, the order of Payment and Delivery can be swapped. In case D comes before P (in a "pay afterwards" scenario: A = D → P or even A → D → P), the risk clearly rests with the seller, and *vice versa*. There is a link here with our classification of payment instruments, in Table 1, as "pay before", "pay now", or "pay later". However, because the distinction in Table 1 only relates to the settlement of the transaction, it does not necessarily reveal much about the chronological sequence of payment and receipt of the goods. Indeed, a consumer who buys physical goods online and pays by means of an online bank transfer – which is a *pay now* payment instrument in terms of settlement – in fact pays first and will receive the goods only a couple of days later. In other words, in the TCM model such a scenario classifies as "pay in advance" (o.c., Figure 2, p. 221).

Finally, concerning r_p (product risk) Liezenberg et al. (o.c., p. 221) argue that the "core characteristics are the value (high/low) and substance (virtual/physical). In particular, the value of the product strongly determines Risk perceived by both actors. High-value products require more guarantees than do low-value products"[vi]. Our first and most important hypothesis builds on this. As will be explained in Section 4, we have first classified the 194 sites in our dataset into sectors, and subsequently grouped the sectors into categories, based on an assessment of whether the average transaction amount in the sector is low, medium, or high; in other words, based on the level of r_p. In line with the above quote, our conjecture is then that sites active in a sector with high product risk, r_p, and thus potentially high payment risk, R_P, will try to mitigate total risk, R, by opting for payment methods for which the timing risk, r_t, is low for the seller (and by avoiding methods with a high r_t), and in this way putting the payment and/or the agreement risk with the buyer. Hence our H1 reads:

H1: the higher the product risk, the higher the probability that e-retailers will opt for payment methods with a low timing risk for the seller.

Given that risk aversion is a common axiom in the economics and management literature, H1 may seem too obvious a hypothesis to test, but in fact it is not. For one, the TCM model has never been tested before. Secondly, and more importantly, payment instruments are no ordinary goods. A merchant who refuses to accept a specific payment instrument stands to lose custom. As documented by Van Hove (2010), there are indications that, within certain limits, merchants will accommodate consumer preferences, particularly in a competitive environment. Arango and Taylor (2008), for example, analyze the results of a stratified survey commissioned by the Bank of Canada and carried out amongst 500 (real-world) merchant representatives. Interestingly, merchant acceptance levels do not reflect merchants' relative preferences. For example, when merchants who accept *all three* payment instruments surveyed (cash, debit and credit) were asked which one they prefer consumers to use the most often, 53 per cent favored debit cards, 39 per cent favored cash, and only 5 per cent favored credit cards - whereas they do accept them. Arango and Taylor also find that, as consumers use a payment instrument more intensively, merchants increasingly value their choice. For example, the more cash-oriented a merchant's business, the lower he will rank debit and credit cards (o.c., p. 16). In short, H1 is not all that obvious; merchants might well be willing to accept a certain degree of risk. A third, and related, reason why H1 is worth examining is that an improved insight into online merchants' attitude towards the different forms of risk would help in gauging their willingness to accept (and pay for) novel payment services such as Klarna that hinge on an alternative distribution of product risk between seller and buyer. As Klarna co-founder Sebastian Siemiatkowski points out: "We realised that making payments in ecommerce had a lot of flaws to it. Sending money to an online merchant, hoping to receive a product that resembles what you saw in the picture is actually a risky undertaking for the consumer" (Milne, 2013). This is why Klarna allows online shoppers to pay via invoice after receiving the goods. Klarna claims this increases conversion.

H1 obviously raises the question *which* online payment methods minimize r_t for the seller. At the end of their article, Liezenberg et al. (2007) apply their framework to a number of context examples and score the most commonly used payment solutions context per context. The example that is most relevant for our purposes is the one about an online purchase of a design clock with a "high value" of EUR 199 (o.c., Table 1, p. 224). For this context, Liezenberg et al. identify bank transfers as low-risk for the seller, and credit cards as high-risk (o.c., Table 3, p. 225). The reason is that the first are guaranteed (in part because P takes place before D, as explained above) and the second not. Indeed, even though surfers who pay by credit card have to enter their card details online, so that here too P seemingly takes place prior to D, in reality, as explained in Section 2, the actual settlement of the payment takes place later, and credit card customers can - legitimately or not - reverse a transaction, resulting in a 'chargeback' (the return of funds to the consumer). Indeed, as Zhang and Li (2004, p. 1078) point out – for the case of the US – "under the Fair Credit Billing Act, buyers have the right to withhold payment on poor-quality or damaged merchandise purchased with a credit card." Credit card buyers can also (claim to) be the victims of fraud, in which case the seller has to refund the sales price, loses the product, cannot recover the original transaction fee, and even faces a new transaction fee for the reverse payment. According to Zhang and Li (ibidem), in the US such chargeback fees typically range from USD 10 to USD 20. More generally, the Zhang and Li article contains an interesting Table – Table 1 on p. 1079 – that provides an overview, for the case of the US, of the protection that individual payment methods provide to both buyers and sellers. Zhang and Li's conclusion from the Table is straightforward: for buyers, credit cards provide more protection than cash-equivalents such as cash, money order, cashier's check, etc.; for sellers, it is the opposite. Given the higher card fraud levels, this holds *a fortiori* in the countries that we study. In line with H1, one would thus expect that e-retailers active in a sector with high product risk are less inclined to accept credit cards, and more inclined to accept bank transfers – or other low-risk payment methods, for that matter. For our purposes, it is important to note that online payments with debit cards or e-money have a low timing risk for the seller because, just like bank transfers, A and P coincide and precede D. COD of physical goods corresponds with generic timing type 3a in Liezenberg et al.'s Figure 2 (o.c., p. 221); that is, A → D = P. Because there is a "simultaneous handover" (D = P), the payment risk for the seller is low. There is, however, an agreement risk. The buyer might on the spot call of the transaction and refuse to pay – for a number of reasons, both real (she is disappointed with the good) or invented (she has second thoughts). If this happens, the seller not only loses a sale but also incurs a loss in delivery cost. The latter is also true when the address is wrong. This probably explains why, on a ++ to -- scale, Liezenberg et al. give cash a '-' for seller risk in their 'pizza order via telephone' scenario (o.c., Table 7, p. 226). Note that credit cards score '--' in the above example of an online purchase of a design clock.

That payment risk effectively matters for e-retailers can be gleaned from a (non-representative) pilot survey conducted by the Social Platform on Payment Systems in the Netherlands (Kosse, 2010, p. 5). Of the 27 merchants who took part in the survey, 8 were web merchants – 5 of which accepted credit cards. In response to an open question about possible reasons why they would stop accepting credit cards, arguments related to payment risk were proffered 3 times: "increase in risks and administrative burden of chargebacks" (2) and "increase in fraud" (1) (o.c., p. 9).[vii]

Moving from payment risk, $R_{P,}$ to delivery risk, R_D - and moving in the direction of our second main hypothesis - it is clear that, as already alluded to in the Introduction, a site's adoption of distribution channels on the one hand and choice of payment methods on the other may be interlinked. It is again tempting to suppose that this holds *a fortiori* for the countries that we study. Indeed, the environment in our five countries is challenging: an underdeveloped ICT infrastructure, fragmented distribution channels, and a bureaucratic legal environment all create problems in e-commerce logistics management. In the traditional socialist system, large state-owned enterprises dominated most industries, including transportation and logistics. Today, transportation facilities in many transition economies are still poorly developed. The national postal system that covers pick-up, transport and delivery of letters and parcels is a relatively cheap method of distribution, but may be problematic in transition countries. In most post-soviet states, the postal system is characterized by poor quality of service. It is functional but cannot be considered secure or reliable enough to provide efficient logistics for e-commerce (Guislain, 2004). Moreover, it is definitely not suited for urgent deliveries because of the scarcity of regional flights (Mayhew, 2007). In line with these remarks, our survey reveals that a substantial portion of the sites have set up delivery options that they can fully control: across all countries, 31% offer in-store pick-up and 19% have a privately delivery service; see Table 3 for definitions. In Uzbekistan, these percentages are even 36% and 39%, respectively. Tellingly, the national postal system is only used in Kazakhstan (by 23% of the local sites).

Concerning the potential symbiotic relationship between delivery and payment methods, we hypothesize that e-retailers that opt for a delivery method with a low delivery risk, R_D, will also opt for a payment method that mitigates their payment risk, R_P:

H2: e-retailers that opt for low-risk delivery methods are more likely to adopt low-risk payment methods.

The rationale behind this hypothesis is straightforward: we take the adoption of low-risk delivery methods to be an indication that the e-retailer is relatively risk-averse and we expect this to be also reflected in his choice of payment method. For example, one would expect merchants who prefer to rely on in-store pick-up to also have a higher preference for COD, which has a lower payment risk then credit cards as buyer and seller 'cross the bridge' at the same time. COD in effect turns a virtual into a physical transaction, thus lowering r_t and r_l – and ultimately both R_P and R_D (Liezenberg et al., 2007, p. 220)[viii], but as pointed out above not necessarily R_A. Note that the relationship to be tested in H2 need not be symmetric; on the contrary even. Indeed, e-retailers who have no problem offering high-risk delivery methods are probably happy to accept low-risk payment methods (as well).

Table 3. Delivery methods: definitions

Method	*Definition*
Postal system	The country's national postal system, which may include products such as Express Mail Service (EMS).
Courier service	An independent delivery service provider similar to DHL or FedEx. Relatively expensive compared to the national postal system. Offers both express and slower surface delivery methods.
Private service	Private delivery service operated by the e-retailer and usually limited to a specific region.
In-store pick-up	Customers visit the e-retailer's physical store or distribution outlet to collect items ordered online. Payment can in principle be done either online or at the time of collection.
Electronic	Delivery of digital goods such as music, video, books or customizable gift-cards.

Source: Authors' own compilation based on prior literature (e.g., Hawk, 2004; Lee and Whang, 2001).

3.2. Other determinants

Although the focus of the paper is on the role of risk, there are obviously several other potential determinants of the adoption of online payment methods by B2C websites. We thus have to control for these factors. To start on the country level, it is clear that whatever the infrastructure of a country, providing payment options that are familiar as well as convenient to customers is a must for e-retailers (Singh, 2002). As Liezenberg et al. (2007, p. 224) put it, “the seller also has to take into account the risk of losing the transaction altogether, when no acceptable Payment and Delivery solutions are offered to the buyer”. In terms of the TCM: e-tailers might seek to lower R_A. Prior research confirms that the popularity of a particular payment method among prospective customers is a vital factor in determining its acceptance by online merchants; see Polasik and Fiszeder (2010) for the case of Poland. Hence, in view of the dramatic inter-country differences in penetration rates observed in Table 2, we expect the degree of (offline) penetration of a payment instrument to positively affect its adoption by e-retailers.

A further justification of this hypothesis can be found in the network externalities theory. In general, network goods are “products for which the utility that a user derives from consumption of the good increases with the number of other agents consuming the good” (Katz and Shapiro, 1985, p. 424). Applied to payment instruments, the network externalities theory implies that consumers will not use a payment instrument as long as they can only pay with it in a limited number of shops, whereas merchants will be reluctant to invest in equipment or software needed to accept the payment instrument unless (they think that) a sufficient number of customers will be interested (Van Hove, 1999).

We also control for two additional (and intuitive) factors, both of which are situated on the website level. For one, merchants who want to sell to foreign markets by definition need to adopt international payment options, credit cards being the prime example. Such merchants might also, as Polasik and Fiszeder (2010) find for the case of Poland, see less need to accept “methods based on domestic settlement systems or personal contact”. Secondly, apart from home delivery, only e-retailers with an offline presence have the ability to allow for payment in person - potentially by means of a range of payment instruments (cash, debit cards, etc.) – and, conversely, might be less inclined accept online payment instruments.

On a final note, it should be pointed out that we were unable to take into account a number of potential determinants because we lacked (sufficiently detailed) data. For one, there is the usability of payment instruments. While this is unlikely to differ on the site or sector level, it might matter on the country level. Some of the e-money solutions that we encountered, for example, differ from one country to another. And even payment instruments that are *in se* identical, such as credit cards, might have a different usability depending on the security measures that are implemented. We did try country dummies to capture this, but these did not yield meaningful results. In order to check for a possible omitted macro-level factor, we also ran our regressions for subsets of countries and for individual countries. Except for pay-roll cards – which are only available in two countries anyway - these robustness checks are only briefly reported in footnotes.

This said, the most glaring omission on our list of variables is the cost of a given payment instrument for the merchant. Not only might this cost differ from one country to another, it might also differ from one sector to another. That costs matter is self-evident. In the small-scale survey for the Netherlands mentioned in 3.2, 3 of the 5 web merchants who accept credit cards spontaneously mentioned "an increase in costs" as a reason why they would stop accepting the cards – an incidence that is on par with the risk-related arguments (Kosse, 2009, p. 9). We come back on the impact of costs in our discussion of the results (in Section 5). Note that Liezenberg et al. (2007, p. 223), for their part, are convinced that "cost and usability considerations for buyer and seller are secondary to the risk assessment of the transaction, making (perceived) Risk the determining factor for the use of payment solutions" – which is precisely what we will try to test.

4. Methodology

4.1. Data collection

Where the data is concerned, in June-August 2010 we set out to content analyze all B2C websites in five Central Asian countries. To find the websites, we first systematically screened the local trade portals (e.g., http://webtrade.kz and http://www.uz) and business directories of each country (i.e., Yellow Pages and Golden Pages). Next, we performed keyword searches on popular search engines such as Google and Yandex. The descriptors used in the searches included: e-commerce, online shop, e-shop, online retail, e-tail (alternately combined with Kazakhstan; Kyrgyzstan; Tajikistan; Turkmenistan; and Uzbekistan). The keyword searches were performed in English, Russian, as well as in local languages. The majority of the websites were found on local web trade portals and on the Russian search engine Yandex. The bulk of the websites' content was in Russian (a language mastered by one of the authors, along with most local languages). Note that this approach for identifying relevant websites has been used by other scholars (e.g., Govers and Go, 2005).

Our initial search produced a total of 308 hits (distributed as follows: Kz=170; Kg=49; Tj=22; Tm=12; Uz=55), all of which were subsequently examined for relevancy. We eliminated all non-transactional websites (that is, sites that did not allow for instant order placement and did not provide payment or delivery options) as well as sites outside the B2C sector. Eventually 194 sites were left (with: Kz=126; Kg=23; Tj=6; Tm=3; Uz=36). Since we have endeavored to make our search as extensive as possible, our dataset should cover just about the entire population of relevant sites at the time, but we can obviously never be entirely sure.

In order to obtain the information on payment and delivery methods that we needed, we analyzed the content of the websites in 2 stages: we first investigated the *Help* or *FAQ* pages and subsequently we set up an account and placed an order (without really going through the check-out). Since the absence or presence of a payment/delivery method is straightforward to observe and easy to code (absence = 0; presence = 1), we saw no need to have the data independently recorded by different observers (Hayes and Krippendorff, 2007, p. 80), and relied on a single visit. Table 4 provides an overview of the codes used.

4.2. Descriptive data on the acceptance of online payment methods

Table 5 and Figure 1 show that – even though they can only be used by domestic consumers - the paper-based offline payment methods are the options most commonly provided by the e-commerce businesses in the region, with 81% of the sites accepting at least one such method in 2010 (see ANYP). Especially bank transfers and COD are popular options, with overall adoption rates of 76% and 42%, respectively. To clarify: an offline, paper-based bank transfer will typically require customers to go to the bank designated by the e-retailer to initiate a money transfer to the vendor's account. Paying at the post office is limited to Kazakh sites. Note that per-country penetration rates can vary from the single to the double, and even more - although the low number of observations for Tajikistan and Turkmenistan calls for prudence. For the three other countries, we performed χ^2 and ANOVA tests to check, respectively, for differences (1) in the proportion of sites that accept a given paper-based instrument, and (2) in the mean number of paper-based instruments that are accepted. None of the differences proved to be statistically significant (p>.05), with the obvious exception of paying at the post office (cf. supra).

Table 4. Payment & delivery variables

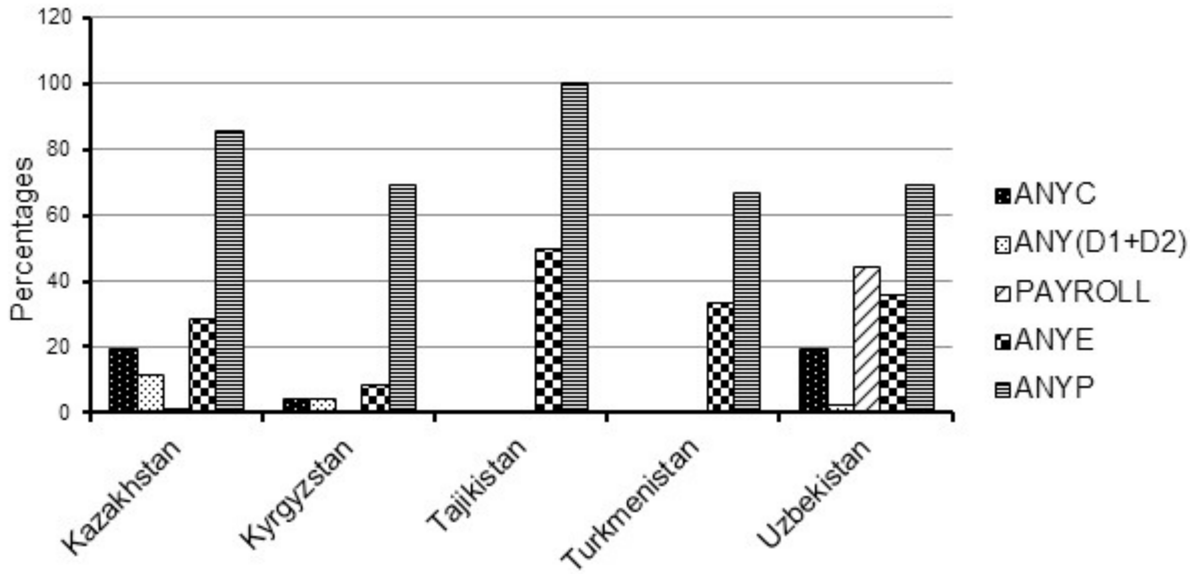
Category		Code	Subcategory
Payment methods	Credit Card	C1	Visa (0/1)
		C2	MasterCard (0/1)
		C3	American Express (0/1)
		C4	Diners Club (0/1)
		C5	Discover (0/1)
		C6	JCB (0/1)
		ANYC	= C1 *or* C2 … *or* C6; binary (0/1)
		TOTALC	= C1 + C2 … + C6; integer, ranges between 0-6
	Debit Card	D1	Visa Electron (0/1)
		D2	Maestro (0/1)
		D3	Payroll card (0/1)
		ANYD	= D1 *or* D2 *or* D3; binary (0/1)
		ANY(D1+D2)	= D1 + D2; binary (0/1)
		TOTALD	= D1 + D2 + D3; integer, ranges between 0-3
	ANY(C+D)		= ANYC *or* ANYD; binary (0/1)
	TOTAL(C+D)		= TOTALC + TOTALD; ranges between 0-9
	E-Money	E1	PayPal (0/1)
		E2	WebMoney (0/1)
		E3	ePay (0/1)
		E4	Other e-money (0/1)
		ANYE	= E1 *or* E2 … *or* E4; binary (0/1)
		TOTALE	= E1 + E2 … + E4; integer, ranges between 0-4
	Paper-based	P1	Cash-on-delivery (0/1)
		P2	Bank transfer (offline) (0/1)
		P3	Pay at post office (0/1)
		P4	Other paper-based (0/1)
		ANYP	= P1 *or* P2 … *or* P4; binary (0/1)
		TOTALP	= P1 + P2 … + P4; integer, ranges between 0-4
	TOTALCAT		= ANYC + ANYD + ANYE + ANYP; integer, ranges between 0-4
	TOTALALL		= TOTALC + TOTALD + TOTALE + TOTALP; integer, ranges between 0-17
Delivery services	LOGISTICS_PRIVATE		Private delivery (0/1)
	LOGISTICS_POSTAL		National mail (0/1)
	LOGISTICS_COURIER		Courier service (0/1)
	LOGISTICS_INSTORE		In-store pick-up (0/1)
	LOGISTICS_OTHER		Other delivery methods (0/1)

Note: in the codes, C stands for 'credit card', D for 'debit card', etc.

All this indicates that B2C sites in Kazakhstan, Kyrgyzstan and Uzbekistan by and large behave similarly in adopting paper-based payment instruments, probably due to similarities in the environment. A practical implication is that in our empirical analysis we decided to focus mainly on electronic payment instruments, where the differences in adoption are greater.

Credit cards, for example, are almost exclusively accepted, and to the same extent, in Kazakhstan and Uzbekistan. The latter is a mild surprise, given that the bulk of the payment cards issued in Uzbekistan are actually debit cards (i.e., payroll cards), many of which cannot be used online (see Section 2). As will be demonstrated in Section 5, the explanation lies with Uzbek sites that target international markets. The picture for debit cards is similar. Again they are accepted almost exclusively in Kazakhstan and Uzbekistan, be it that the type differs: Visa Electron and Maestro in Kazakhstan vs. local payroll cards in Uzbekistan.[ix]

Figure 1. Adoption of payment methods by B2C e-retailers



Where e-money is concerned, it can be seen that options such as WebMoney, ePay, and PayPal are widely accepted by sites in Kazakhstan and Uzbekistan, and to a lesser extent by Kyrgyz B2C ventures (only 2 sites).[x] With an overall penetration rate of 21%, WebMoney is clearly the most widely adopted, while ePay is only accepted by Kazakh e-retailers (8.7%). A χ^2 test for the overall adoption of e-money options - that is, for ANYE – shows that the difference in adoption between the 3 countries is moderately significant.[xi] This could be due to the higher development of the non-banking sector of instant payments in Uzbekistan, where there are several e-money schemes such as Paynet, E-pay, Fast-pay, Unipay, Cyberplat, WebMoney, Mobliss, PayCarta, and the national eKarmon system (ICT Policy Project, 2008). These instruments, which not only allow to purchase goods from online stores, but also to top-up mobile phone credit, and pay for Internet access or international telephony services, are becoming increasingly popular in Uzbekistan.

In the analytical part of the paper (Section 5), we try to explain the adoption of a selection of the above payment methods by means of logit analysis. We do so using explanatory variables on both the site, sector, as well as country level. These variables are defined in the next subsection. Definitions of all the variables, together with data sources, can be found in Table A1 in the Appendix. Descriptive statistics can be found in Table A2 and correlations in Tables A3a and A3b.

Table 5. Payment options provided by B2C e-commerce websites

Category	Subcategory	KZ n (%)*	KG n (%)*	TJ n (%)*	TM n (%)*	UZ n (%)*	**Total n (%)****
Credit cards	Visa	25 (19.8)	1 (4.3)	0 (.0)	0 (.0)	7 (19.4)	**33 (17.0)**
	MasterCard	24 (19.0)	1 (4.3)	0 (.0)	0 (.0)	7 (19.4)	**32 (16.5)**
	American Express	6 (4.8)	0 (.0)	0 (.0)	0 (.0)	5 (13.9)	**11 (5.7)**
	Diners Club	4 (3.2)	0 (.0)	0 (.0)	0 (.0)	0 (.0)	**4 (2.1)**
	Discover	0 (.0)	0 (.0)	0 (.0)	0 (.0)	1 (2.8)	**1 (0.5)**
	JCB	0 (.0)	0 (.0)	0 (.0)	0 (.0)	1 (2.8)	**1 (0.5)**
	ANYC	***25 (19.8)***	***1 (4.3)***	***0 (.0)***	***0 (.0)***	***7 (19.4)***	***33 (17.0)***
Debit cards	Visa Electron	11 (8.7)	1 (4.3)	0 (.0)	0 (.0)	0 (.0)	**12 (6.2)**
	Maestro	12 (9.5)	0 (.0)	0 (.0)	0 (.0)	1 (2.8)	**13 (6.7)**
	Payroll card	2 (1.6)	0 (.0)	0 (.0)	0 (.0)	16 (44.4)	**18 (9.3)**
	ANYD	***16 (12.79)***	***1 (4.3)***	***0 (.0)***	***0 (.0)***	***16 (44.4)***	***33 (17.0)***
	ANY(D1+D2)	***16 (11.9)***	***1 (4.3)***	***0 (.0)***	***0 (.0)***	***1 (2.8)***	***17 (8.8)***
	ANY(C+D)	**25 (19.8)**	**1 (4.3)**	**0 (.0)**	**0 (.0)**	**22 (61.1)**	**48 (24.7)**
E-money	PayPal	3 (2.4)	0 (.0)	0 (.0)	1 (33.3)	6 (16.7)	**10 (5.2)**
	WebMoney	24 (19.0)	2 (8.7)	3 (50.0)	1 (33.3)	11 (30.6)	**41 (21.1)**
	ePay	11 (8.7)	0 (.0)	0 (.0)	0 (.0)	0 (.0)	**11 (5.7)**
	Other e-money	5 (4.0)	0 (.0)	0 (.0)	1 (33.3)	1 (2.8)	**7 (3.6)**
	ANYE	***36 (28.6)***	***2 (8.7)***	***3 (50.0)***	***1 (33.3)***	***13 (36.1)***	***55 (28.4)***
Paper-based	Cash-on-delivery	99 (78.6)	16 (69.6)	6 (100.0)	1 (33.3)	25 (69.4)	**147 (75.8)**
	Bank transfer	54 (42.9)	6 (26.1)	3 (50.0)	2 (66.7)	17 (47.2)	**82 (42.3)**
	Pay at post office	14 (11.1)	0 (.0)	0 (.0)	0 (.0)	0 (.0)	**14 (7.2)**
	Other paper-based	17 (13.5)	2 (8.7)	0 (.0)	0 (.0)	0 (.0)	**19 (9.8)**
	ANYP	***108 (85.7)***	***16 (69.6)***	***6 (100.0)***	***2 (66.7)***	***25 (69.4)***	***157 (80.9)***
Number of websites		**126**	**23**	**6**	**3**	**36**	**194**

* Number and percentage of websites in a country that accept a payment option
** Number and percentage of the total number of websites that accept a payment option

4.3. Definitions of explanatory variables

As explained, the explanatory variables at the core of our analysis relate to risk. As already briefly mentioned in Section 3.1, in order to construct our variable for PRODUCT_RISK, we first classified the 194 sites in our dataset into 15 sectors – following the classification on the InternetRetailer website[xii] - and subsequently grouped the sectors into 3 categories, based on an assessment of whether the average transaction amount in the sector is low, medium, or high. In order to do this as objectively as possible, we followed a multiple-rater approach. Three individuals – the two authors and a marketing colleague specialized in retailing - first rated all sectors independently. On comparing the individual ratings, it emerged that there was immediate agreement on 11 of the 15 sectors. The disagreements were resolved by jointly revisiting a random selection of sites in the 4 sectors concerned. This second round also impelled us to split up the sector ‘Housewares/Home Furnishings’ into two separate sectors, as there proved to be substantial differences in the values of the products listed. A complete list of the sectors, together with their classification, can be found in Table A4 in the Appendix.

It is clear that this proxy can be criticized. We realize that the price range of products in a sector can be quite large and that, as a result, the price ranges of different sectors can, and in many cases will, overlap. For instance, certain computer parts and accessories (categorized as ‘high risk’ in our classification) might be cheaper than some health and beauty products (that are categorized as ‘low risk’). However, what we try to capture is not so much inter-sector differences in product values, but rather in transaction sizes. In their model, Liezenberg et al. (2007, p. 221) may reason in terms of an individual product – cf. “the value of *the product*” in Section 3.1 - in reality ‘product risk’ is determined by the content of the shopping cart and should thus perhaps rather be thought of as ‘order risk’. Also, e-retailers typically cannot (or will not) prevent customers from using a specific payment instrument for higher transaction values: once a web merchant accepts a certain risky payment instrument, the risk is *de facto* not limited to low-value orders. Hence, one needs to take into account the full price range of the sector. Given that fraudsters have an incentive to maximize the value of their order – without, however, raising suspicion – it could even be argued that the upper part of the price range is more relevant. Such fraud behavior also throws a different light on the fact that our proxy is measured at the sector level (and thus ignores possible heterogeneity among e-retailers within a sector). Clearly, directly asking merchants about average transaction sizes and/or perceived risk levels would have been a more objective way of measurement, but an *ex ante* small-scale test indicated that response levels would be very low, resulting in a loss of too many observations.[xiii]

Importantly, we tried two variants of our PRODUCT_RISK variable: one with three categories as just explained (‘low’, ‘medium’, and ‘high’) as well as a binary variable in which the ‘medium’ and ‘high’ categories were grouped together. Note that the four initial disagreements between the raters all related to whether a specific sector should be placed in the ‘medium’ or ‘high’ category. In other words, for the binary PRODUCT_RISK variable there was full agreement from the start. Note also that this approach is not dissimilar from the one followed by Basu and Muylle (2002) and Muylle and Basu (2004) in their studies for the US. These authors distinguish industries selling inexpensive and expensive products based on whether the average sales price is less than USD 50 or not (Basu and Muylle, 2002, p. 384). Our binary variable proved to yield the strongest results and is therefore the one that we will concentrate upon when presenting the results. If and when the results obtained with the alternative variable show relevant differences, this is indicated explicitly.

As explained in 3.1, we also constructed an index to gauge the risk associated with the delivery methods used by our e-retailers. In doing do, we considered electronic delivery, in-store pick-up, and private delivery to be low-risk (value = 1), as the e-retailer remains fully in control. We assumed that outsourcing of delivery, even to reliable partners, increases the risk. Specifically, we deemed the use of courier services to be medium-risk (value = 2), and the use of the national postal system - which is reportedly not very reliable, see 3.1 – to be high-risk (value = 3). In our DELIVERY_RISK variable, every merchant was then given a 'risk coefficient' corresponding to the highest-risk delivery method that he uses. For example, a merchant who amongst other methods makes use of courier services, but not of the postal system, receives a 2.

Turning to our control variables, due to data scarcity we were only able to quantify the degree of (offline) penetration of payment cards and bank accounts; see Table 2. For e-money products we lacked the necessary data. Where payment cards are concerned, we constructed several variants, so as to be able to focus on specific types of cards. For one, %CARDS_INTERNAT is the total number of international cards in circulation divided by total population. %CARDS_LOCAL is a similar variable for local cards. An important drawback of %CARDS_INTERNAT is that it does not distinguish between credit and debit cards. We therefore relied on the World Bank's *Global Financial Inclusion (Global Findex) Database* and the EBRD's *Life in Transition (LiTS) survey II* to construct more specific variables; see Table A1 for details and Table 2 for actual numbers. Since the penetration of payment instruments is often linked with the level of economic development of a country, we also tried GDP per capita (GDPCAP) and the Human Development Index (HDI) as alternative country variables.

All other remaining explanatory variables are simple binary dummies. OFFLINE_PRESENCE equals 1 for bricks-and-clicks companies, and 0 for so-called pure-plays. INTERNAT_CUR, INTERNAT_LNG, and INTERNAT_DELIV are three alternative dummies that try to gauge whether a site targets international markets or not, resp. by looking at whether prices are (also) mentioned in foreign currency, whether the site is (also) available in one or more foreign languages, and whether the site states explicitly that they deliver internationally. Finally, LOGISTICS_COURIER and the like are simply ways to test links between payment and delivery methods on the individual level, rather than just in the aggregate – by means of DELIVERY_RISK.

5. Results

In Tables 6-9 we report our logistic regression results in the most obvious way; that is, payment instrument by payment instrument. We do not, however, discuss them in this order. Rather we discuss them per explanatory variable – across payment instruments. We start with the predictor variables that are directly related to our hypotheses, namely PRODUCT_RISK (in 5.1) and DELIVERY_RISK (in 5.2). Next we briefly discuss the control variables (in 5.3).

Note that we have not tried to explain the adoption of all payment instruments listed in Table 4. As explained in 4.2, the inter-country variation in the overall acceptance of paper-based payment instruments (ANYP) is low. Moreover, ANYP proved to be too diverse a category, comprising COD as well as bank transfers. Of the paper-based instruments, we therefore only cover COD. Similarly, ANYD is also very diverse, comprising as it does both local and international debit cards, which clearly target a different audience. Here we decided to concentrate on payroll cards (which are very popular in Uzbekistan) rather than on Visa Electron and Maestro - purely because we have better data for certain explanatory variables, as will become clear.

In all models below, the dependent variable is the adoption (Y/N) of a given payment instrument by online vendors. Hence, a negative coefficient indicates that the predictor acts as an obstacle, while a positive sign suggests the opposite. Judging from the Cox & Snell and Nagelkerke goodness-of-fit measures, the preferred models fit the data reasonably well. The likelihood ratio (Chi-square) statistics and associated *p* values suggest that jointly our explanatory variables have a significant impact on the adoption of the selected payment instruments.

5.1. Product risk

In Hypothesis 1, we assumed that e-retailers active in a sector with high product risk are less prone to accept high-risk payment methods. Our results for ANYC in Table 6 show that PRODUCT_RISK indeed has a negative and highly significant impact on the acceptance of credit cards, which are 'pay afterwards' and thus high-risk for merchants (as explained in 3.1).[xiv]

Conversely, given H1, one would expect PRODUCT_RISK to have a positive impact on the adoption of payment instruments that classify as either ‘pay in advance’ (such as e-money and debit cards) or ‘simultaneous handover’ (such as COD). In Tables 7-9 it can be seen that we do find such an impact for payroll cards (D3), but *not* for e-money (ANYE) or COD.

For the latter two, PRODUCT_RISK is insignificant (and even has the wrong sign).[xv] This can, however, be explained. To start with ANYE, there is first the fact that this category also contains PayPal, which these days is mainly used not as an electronic wallet, but rather as an indirect way for small merchants to accept credit cards. This may go some way to explain the negative sign. Second, ‘real’ e-money schemes by their very nature typically do not target larger-value payments, thus limiting PRODUCT_RISK. Turning to COD, the explanation would seem to be a lack of variation: overall, no less than 76% of online merchants offer this payment option. The picture that emerges is one where many sites have little choice but to accept paper-based payment instruments - in order not to leave the unbanked in the cold.

Finally, the consistent positive impact of PRODUCT_RISK on the adoption of payroll cards in Table 7 would at first sight seem to confirm H1. There is, however, a crucial caveat, which incidentally also applies to the result obtained for credit cards.[xvi] The caveat is that there is a competing explanation besides product risk, namely the cost for the merchant of accepting the cards – a variable that, as pointed out in 3.2, we could not control for because we lacked sufficiently detailed data.

Table 6: Determinants of ANYC (all countries; N = 194)

Dependent variable	ANYC								
Specification	1	2	3	4	5	6	7	8	9
Site-specific variables									
CONSTANT	-947	-.672	-.352	-1.261	-1.027	-.655	-1.783*	-1.743*	-1.120
Sig.	(.304)	(.430)	(.665)	(.203)	(.250)	(.450)	(.073)	(.064)	(.211)
OFFLINE_PRESENCE	-.686*	-.808**	-.865**	-.831*	-.936**	-.950**	-.829*	-.942**	-.949**
Sig.	(.100)	(.050)	(.044)	(.056)	(.031)	(.032)	(.057)	(.030)	(.031)
INTERNAT_CUR	1.181**			1.058*			.958		
Sig.	(.047)			(.095)			(.120)		
INTERNAT_LNG		1.042*			1.094*			1.102**	
Sig.		(.051)			(.051)			(.048)	
INTERNAT_DELIV			1.975***			1.683***			1.585**
Sig.			(.001)			(.009)			(.014)
LOGISTICS_COURIER				1.538***	1.662***	1.362**			
Sig.				(.006)	(.004)	(.017)			
DELIVERY_RISK							.930***	1.022***	.768**
Sig.							(.006)	(.003)	(.027)
Sector-specific variables									
PRODUCT_RISK	-1.225***	-1.176***	-1.246***	-1.460***	-1.460***	-1.467***	-1.392***	-1.367***	-1.394***
Sig.	(.004)	(.006)	(.004)	(.001)	(.001)	(.001)	(.002)	(.003)	(.002)
Country-specific variables									
%CARDS_CREDIT_FINDEX	.216***	.180**	.147**	.169*	.130*	.111	.132	.101	.091
Sig.	(.010)	(.016)	(.050)	(.051)	(.090)	(.150)	(.134)	(.209)	(.253)
Valid observations	194	194	194	194	194	194	194	194	194
Model Fitting Information									
-2 Log Likelihood	156.059	156.338	149.436	146.954	146.040	142.742	147.978	146.612	144.328
Chi-Square	20.888***	20.610***	27.511***	29.993***	30.907***	34.206***	28.970***	30.336***	32.619***
df	4	4	4	5	5	5	5	5	5
Sig.	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Hosmer and Lemeshow Test: Chi-Square	3.072	1.039	1.505	6.859	3.123	5.642	8.341	6.246	10.629
df	6	6	7	8	8	7	7	7	8
Sig.	(.800)	(.984)	(.982)	(.552)	(.926)	(.582)	(.303)	(.511)	(.224)
Pseudo R-Square									
Cox & Snell R	.102	.101	.132	.143	.147	.162	.139	.145	.155
Nagelkerke R Square	.171	.168	.221	.239	.246	.270	.232	.242	.259
Percentage Correct									
% correct P=1	6.1	6.1	21.2	18.2	21.2	27.3	18.2	21.2	24.2
% correct P=0	100.0	98.8	98.8	97.5	98.1	97.5	99.4	99.4	98.8
% overall correct	84.0	83.0	85.6	84.0	85.1	85.6	85.6	86.1	86.1

Note: Regressions were run with binary logit. P-values are reported in parentheses. *, **, *** indicate significance levels of 10%, 5%, and 1% respectively.

Table 7: Determinants of PAYROLL (a = UZ, N = 36; b = UZ & KZ, N = 162)

Dependent variable	PAYROLL[a]						PAYROLL[b]					
Specification	1	2	3	4	5	6	7	8	9	10	11	12
Site-specific variables												
CONSTANT	-3.946**	-5.683**	-4.754**	-3.358	-5.713**	-4.927**	-9.036***	-9.957***	-10.437***	-10.607***	-12.004***	-12.106***
Sig.	(.037)	(.017)	(.013)	(.104)	(.023)	(.015)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
OFFLINE_PRESENCE	1.459	1.910**	1.811**	1.614*	1.905**	1.740*	.969	1.429*	1.552**	.889	1.343*	1.413*
Sig.	(.118)	(.025)	(.036)	(.098)	(.028)	(.053)	(.232)	(.057)	(.045)	(.279)	(.079)	(.073)
INTERNAT_CUR	-2.394*			-2.684**			-2.497**			-2.277*		
Sig.	(.051)			(.046)			(.040)			(.061)		
INTERNAT_LNG		.610			.605			.322			.084	
Sig.		(.673)			(.677)			(.789)			(.947)	
INTERNAT_DELIV			-18.618			-18.890			1.241			.566
Sig.			(.999)			(.999)			(.324)			(.682)
DELIVERY_RISK				-.729	.035	.259				.855	1.065	.965
Sig.				(.515)	(.969)	(.788)				(.264)	(.140)	(.204)
Sector-specific variables												
PRODUCT_RISK	2.139**	2.600**	2.169**	2.357**	2.593**	2.096**	2.191**	2.443**	2.546***	2.079**	2.328**	2.427**
Sig.	(.035)	(.032)	(.027)	(.032)	(.035)	(.039)	(.023)	(.022)	(.008)	(.032)	(.032)	(.014)
Country-specific variables												
%CARDS_LOCAL	a	a	a	a	a	a	.212***	.195***	.204***	.238***	.231***	.231***
Sig.							(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Valid observations	36	36	36	36	36	36	162	162	162	162	162	162
Model Fitting Information												
-2 Log Likelihood	29.769	34.545	34.334	29.325	34.543	34.262	50.378	56.032	55.284	49.097	53.732	53.578
Chi-Square	19.692***	14.917***	15.127***	20.136***	14.918***	15.199***	62.643***	56.990***	57.737***	63.924***	59.289***	59.444***
df	3	3	3	4	4	4	4	4	4	5	5	5
Sig.	(.000)	.002	(.002)	(.000)	(.005)	(.004)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Hosmer and Lemeshow Test:	18.160***	9.122**	11.043	28.860***	10.178*	12.086	12.813	7.097	14.350**	5.149	10.857	6.400
df	4	3	3	5	5	6	6	6	7	8	8	8
Sig.	(.001)	(.028)	(.011)	(.000)	(.070)	(.060)	(.046)	(.312)	(.045)	(.742)	(.210)	(.603)
Pseudo R-Square												
Cox & Snell R	.421	.339	.343	.428	.339	.344	.321	.297	.300	.326	.306	.307
Nagelkerke R Square	.564	.454	.459	.574	.454	.461	.639	.590	.597	.649	.610	.612
Percentage Correct												
% correct P=1	87.5	75.0	75.0	87.5	75.0	75.0	77.8	66.7	66.7	77.8	66.7	66.7
% correct P=0	85.0	95.0	95.0	95.0	95.0	95.0	97.9	93.3	99.3	97.9	97.9	97.9
% overall correct	86.1	86.1	86.1	91.7	86.1	86.1	95.7	95.7	95.7	95.7	94.4	94.4

a. Only Uzbekistan is included in models 1-6, so %CARDS_LOCAL is constant.ote: Regressions were run with binary logit. P-values are reported in parentheses. *, **, *** indicate significance levels of 10%, 5%, and 1% respectively.

TABLE 8: Determinants of ANYE (all countries; N = 194)

Dependent variable	ANYE					
Specification	1	2	3	4	5	6
Site-specific variables						
CONSTANT	-6.043**	-1.326	-.068	-4.292	.420	1.214
Sig.	(.045)	(.579)	(.997)	(.170)	(.867)	(.626)
OFFLINE_PRESENCE	-1.220***	-1.340***	-1.400***	-1.315***	-1.436***	-1.457***
Sig.	(.001)	(.000)	(.000)	(.000)	(.000)	(.000)
INTERNAT_CUR	2.424***			2.350***		
Sig.	(.000)			(.000)		
INTERNAT_LNG		.875*			.936*	
Sig.		(.075)			(.064)	
INTERNAT_DELIV			1.789***			1.444**
Sig.			(.005)			(.029)
DELIVERY_RISK				.748**	.839***	.647**
Sig.				(.013)	(.004)	(.028)
Sector-specific variables						
PRODUCT_RISK	-.184	-.299	-.338	-.328	-.424	-.459
Sig.	(.648)	(.430)	(.372)	(.427)	(.274)	(.234)
Country-specific variables						
HDI	8.295*	2.164	.403	4.102	-2.357	-2.876
Sig.	(.053)	(.530)	(.908)	(.377)	(.541)	(.455)
Valid observations	194	194	194	194	194	194
Model Fitting Information						
-2 Log Likelihood	190.352	209.781	204.313	183.899	200.918	199.312
Chi-Square	40.986***	21.558***	27.025***	47.439***	30.421***	32.026***
df	4	4	4	5	5	5
Sig.	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Hosmer and Lemeshow Test: Chi-Square	10.855*	9.760	4.642	9.186	6.991	10.107
df	6	7	6	8	8	8
Sig.	(.093)	(.203)	(.590)	(.327)	(.538)	(.258)
Pseudo R-Square						
Cox & Snell R	.190	.105	.130	.217	.145	.152
Nagelkerke R Square	.273	.151	.187	.311	.208	.218
Percentage Correct						
% correct P=1	34.5	10.9	12.7	45.5	32.7	32.7
% correct P=0	97.1	96.4	98.6	93.5	94.2	95.0
% overall correct	79.4	72.2	74.2	79.9	76.8	77.3

Note: Regressions were run with binary logit. P-values are reported in parentheses. *, **, *** indicate significance levels of 10%, 5%, and 1% respectively.

Table 9: Determinants of COD (all countries; N = 194)

Dependent variable	COD								
Specification	1	2	3	4	5	6	7	8	9
Site-specific variables									
CONSTANT	1.301*	1.117	.774	5.314*	3.292	2.383	.915	-.050	-.830
Sig.	(.104)	(.150)	(.286)	(.063)	(.216)	(.352)	(.712)	(.983)	(.712)
OFFLINE_PRESENCE	.142	.241	.240	.068	.281	.260	.140	.243	.243
Sig.	(.684)	(.481)	(.481)	(.866)	(.466)	(.499)	(.687)	(.476)	(.475)
INTERNAT_CUR	-.856*			-1.572***			-.883**		
Sig.	(.073)			(.005)			(.064)		
INTERNAT_LNG		-.716			-.876			-.726	
Sig.		(.138)			(.108)			(.132)	
INTERNAT_DELIV			-.297			-1.871**			-.290
Sig.			(.637)			(.020)			(.643)
DELIVERY_RISK				2.172***	2.006***	2.222***			
Sig.				(.005)	(.000)	(.000)			
Sector-specific variables									
PRODUCT_RISK	-.125	-.138	-.022	-.504	-.490	-.442	-.121	-.131	-.012
Sig.	(.752)	(.729)	(.955)	(.268)	(.285)	(.320)	(.758)	(.742)	(.975)
Country-specific variables									
GDPCAP	.000	.000	.000						
Sig.	(.703)	(.430)	(.309)						
HDI				-9.798**	-6.819*	-6.086	.743	2.048	2.778
Sig.				(.022)	(.088)	(.124)	(.831)	(.534)	(.395)
Valid observations	194	194	194	194	194	194	194	194	194
Model Fitting Information									
-2 Log Likelihood	210.221	211.238	213.134	168.758	174.081	171.596	210.320	211.473	213.440
Chi-Square	4.607	3.590	1.694	46.070***	40.747***	43.231***	4.508	3.355	1.387
df	4	4	4	5	5	5	4	4	4
Sig.	(.330)	(.464)	.792	(.000)	(.000)	(.000)	(.342)	(.500)	(.846)
Hosmer and Lemeshow Test: Chi-Square	7.678	16.323	12.461	9.292	11.653	9.760**	6.073	15.148**	13.257
df	6	6	7	7	7	7	5	6	7
Sig.	(.263)	(.012)	(.086)	(.232)	(.113)	(.203)	(.299)	(.019)	(.066)
Pseudo R-Square									
Cox & Snell R	.023	.018	.009	.211	.189	.200	.023	.017	.007
Nagelkerke R Square	.035	.027	.113	.316	.283	.298	.034	.026	.011
Percentage Correct									
% correct P=1	100.0	100.0	100.0	92.5	92.5	92.5	100.0	100.0	100.0
% correct P=0	.0	.0	.0	48.9	44.7	46.8	.0	.0	.0
% overall correct	75.8	75.8	75.8	82.0	80.9	81.4	75.8	75.8	75.8

Note: Regressions were run with binary logit. P-values are reported in parentheses. *, **, *** indicate significance levels of 10%, 5%, and 1% respectively.

To start with credit cards, it is important to realize that merchant fees for such cards are typically *ad valorem* - that is, a percentage of the transaction value - rather than fixed fees per transaction. According to MasterCard, merchant fees for online credit card payments are 1.5%-2% in Kyrgyzstan and around 4% in Uzbekistan.[xvii] According to a contact at Kazkommertsbank, merchants in Kazakhstan face a fee of 3.5% for MasterCard and Visa cards, and 4.5% for American Express cards. Finally, according to a contact at VneshEconom Bank, fees for Visa credit card payments in Turkmenistan would even be 5%. Regardless of their precise level, such *ad valorem* fees pose a tremendous problem for our analysis.[xviii] Indeed, higher (average) transaction amounts (in a sector) not only increase the product and payment risk involved (which is what we try to capture), but also raise the credit card fees (which are absent from our analysis). In short, the negative link between PRODUCT_RISK and the acceptance of credit cards in Table 6 may be due to risk, costs, or both. And, as far as we can see, the two explanations are just about impossible to disentangle because credit card fees are *ad valorem* precisely because the risk for the card companies is proportional to the amount of the payment.

Things are slightly different for (local) debit cards, but again there are interpretation problems. In Table 7, we try to explain the acceptance of so-called payroll cards in Uzbekistan (models 1-6), and Uzbekistan and Kazakhstan combined (models 7-12). According to a contact at Asaka Bank, merchants in Uzbekistan who want to accept the local payroll card only have to buy, lease or rent a POS terminal. There are no monthly or yearly fees for accepting payments, and no per-transaction fees whatsoever.[xix] This would seem to solve our interpretation problem: as merchants face no per-transaction costs, the positive impact of PRODUCT_RISK can apparently only be due to risk: high risk drives merchants to a less risky payment instrument. At first sight, the results in models 7-12, where Kazakhstan is added to the sample, would only seem to strengthen this conclusion. Indeed, according to a contact at Halykbank, merchant fees for the local Altin card, for example, are 1%-2%, depending on which bank has issued the card. Hence, just as in the case of credit cards, the higher the value of the goods sold, the higher the merchant fee becomes in absolute terms. If costs were the driver, one would thus expect to see a *negative* impact of PRODUCT_RISK in models 7-12. Hence, apparently the positive impact that we find can only be due to risk, not to cost. There is, however, again a caveat, namely that merchants' interest in a given payment instrument, ceteris paribus, depends not only on the acceptance cost of the payment instrument itself, but also on that of potential substitutes. Let us take Kazakhstan as an example. In Kazakhstan, merchant fees for credit and payroll cards are, respectively 3.5%-4.5% and 1%-2%. In other words, there is a cost difference of 1.5%-3.5%. As the transaction amount increases, the cost difference becomes larger in absolute terms. Hence, the higher the average value of the goods sold in a sector – the higher the PRODUCT_RISK – the more attractive it is for a Kazakh merchant to adopt debit cards instead of credit cards. In short, the positive link between PRODUCT_RISK and the acceptance of payroll cards that we find in models 7-12 of Table 7 might still simply be due to cost - to the extent that credit and debit cards really are substitutes, that is.

Fortunately, on closer scrutiny Uzbekistan – which is considered separately in models 1-6 - proved to provide us with a very specific environment where it *is* possible to draw clear-cut conclusions. For one, as mentioned in Section 2, there are hardly any credit cards in circulation in Uzbekistan, so that credit cards are not much of a substitute for debit cards. Second, and more importantly, from contacts with four major local commercial banks we learned that local businesses are simply not allowed to accept credit card payments because such payments involve transactions in USD.[xx] Only selected businesses such as hotels, travel agencies and duty-free shops at airports are allowed to accept US dollars and thus credit cards. Upon inspection of our database, we noticed that the 7 Uzbek websites that accept credit cards all clearly target an international audience and sell local handicrafts.[xxi] Third, to repeat, Uzbek merchants face no fees for accepting payroll cards. In short, we are presented with a natural experiment of sorts: the cost of the payment instrument itself does not play a role (because there is no variable cost), nor does the cost of what would appear to be the closest substitute (because it is no substitute). Hence, at least in the case of Uzbekistan, the positive impact of PRODUCT_RISK on the acceptance of debit cards effectively seems to be due to risk.[xxii] By extension, the negative impact of the same variable on the acceptance of credit cards is probably at least partly due to risk.

As already alluded to in the Introduction, possible points of comparison for our results are few and far between. We are only aware of two. For one, Basu and Muylle (2002, p. 391) find in a univariate analysis for the US that "Web retailers of high-cost products provide more extensive support for online payment", a category that comprises online credit card payments (o.c., p. 383). This result is confirmed in their follow-up study with 2002 data (Muylle and Basu, 2004, p. 108). Neither study makes mention of a difference in support for offline payment, which suggests that the difference is not significant. Offline payment refers to checks, cash, wire, and offline credit card payments. This said, Basu and Muylle's result - which at first sight would seem to clash with ours –

is actually not very comparable, and there are a number of reasons that might explain the discrepancy. First, Basu and Muylle's finding relates to a different country (the US) and a different period (1999-2002). Second, their 'online payment' category comprises "e-wallets, shopping cart mechanisms, online credit card payments, smart card systems, e-cash, and payment processes through trusted third parties" (o.c., p. 383); that is, a very diverse set of instruments, with different risk profiles. (And shopping cart mechanisms are not even a payment instrument.) But then Basu and Muylle's justification for looking into differences between low- and high-cost product industries does not lie with risk, but rather with the extent of consumer involvement (o.c., p. 384).[xxiii]

The study by Zhang and Li (2006) provides a second (partial) point of comparison. Zhang and Li analyze 260 eBay transactions and use probit analysis to explain whether the seller offered a credit card payment option, either via PayPal, via Billpoint (at the time eBay's in-house alternative to PayPal), or seller-processed. In Zhang and Li's results – in Table 5 on p. 1085 – the price of the product sold has a positive sign, but the variable is not significant. This may be because they study transactions on eBay, which is in essence a P2P setting with few 'real' merchants (in Zhang and Li's dataset seller-processed credit card transactions account for only 1.54% of the total number of transactions; see Table 3 on p. 1082). For individuals wanting to accept payments online on eBay, PayPal or Billpoint are in fact the only options. In order to be able to directly accept credit (or debit) cards, one would have to apply for accreditation as a merchant by card companies. A second explanation may lie in the fact that the variation in the prices observed by Zhang and Li may be more limited than in the general economy.

5.2. Delivery risk

In Hypothesis 2 we posited that e-retailers who opt for a delivery method with a low delivery risk for the seller are relatively risk-averse in general, and would thus also be more likely to adopt low-risk payment methods. The positive and highly significant impact of DELIVERY_RISK on the acceptance of (risky) credit cards in Table 6 is perfectly in line with this hypothesis: less risk-averse merchants are more likely to adopt high-risk payment methods. Models 4-6 provide more detail: there is a positive link between the use of courier services (risk score = 2) and ANYC. Turning to Table 7, the absence of a significant impact of DELIVERY_RISK on the acceptance of (low-risk) payroll cards is also plausible. Indeed, as pointed out when developing H2 in 3.1, the tested relationship need not be symmetric as e-retailers who have no problem offering high-risk delivery methods are probably happy to accept low-risk payment methods as well. To further corroborate this, we also ran regressions - not reported here - for the total number of payment options provided by the websites, TOTALALL (see Table 4 for a definition). To be clear: the variable TOTALALL is computed on the level of *individual* payment options. This implies that a site that accepts, say, Visa, MasterCard, American Express, Visa Electron, Maestro, WebMoney, as well as COD, gets a value of 7. As an alternative, we also computed a similar variable on the level of *categories* (namely TOTALCAT), implying that the site in the example above now gets a value of 4 – as it accepts payment options in the categories C, D, E, and P. In both cases, DELIVERY_RISK has a positive and highly significant impact, indicating that less risk-averse merchants offer more payment options. Although this cannot really be deduced from the regressions, these results convey the image that, on average, less risk-averse merchants, like all others, offer the safer payment options, but *on top of* these also accept a number of more risky instruments. As an aside, it can be noted that when in models 1-3 in Table 7 OFFLINE_PRESENCE is replaced by LOGISTICS_INSTORE (results not reported), the latter has a positive coefficient that is significant at the 5% level, thus revealing the natural fit between in-store pick-up and payment by means of a payroll card (which, to repeat, cannot be used online). Building on this, models 1-3 in Table 9, predictably, also reveal a natural fit between LOGISTICS_INSTORE and COD. These two results are in line with the findings of Polasik and Fiszeder (2010) for the case of Poland: “the usage of traditional delivery channels, parallel with the Internet [such as shops, salons, branches, registered offices, small Points of Sale, or sales representatives], has a significantly positive impact on the acceptance of cash on delivery, card payment, and payment in person”.

Note that there is an obvious endogeneity issue here (and in other regressions below that link individual payment and delivery methods). Clearly, the results should not be seen as implying a causal relationship running from delivery to payment methods. It is plausible that e-retailers determine both simultaneously. As a matter of fact, we also ran regressions with the LOGISTICS variables as the dependent variable (not reported) and found broadly similar results.

Turning to ANYE (in Table 8), here the positive impact of DELIVERY_RISK actually surprises, as e-money is (normally) a low-risk payment option for the merchant, given that it is (normally) pre-paid. However, just as for PRODUCT_RISK, the presence of PayPal in the e-money category may again be a disturbing factor, PayPal these days being more akin to (high-risk) credit cards than (low-risk) e-money. Part of the explanation might also be that risk-prone merchants are less reluctant to adopt the more innovative payment instruments. Interestingly, there is a strong positive correlation between ANYE and ANYC (.482***). Finally, in Table 9 there is again a counterintuitive positive impact of DELIVERY_RISK on a low-risk payment option, namely cash-on-delivery. A large part of the explanation lies in the fact that, where Kazakhstan is concerned, there is a positive impact, significant at the 5% level, of LOGISTICS_POST – deemed the most risky delivery method (see 4.3) - on COD (results not reported). Use of the national postal system and COD seems to be a ‘natural’ combination in this country. Note that Kazakhstan accounts for 126 of the 194 observations in Table 9 (which explains why the impact of LOGISTICS_POST is also visible in the full sample; results not reported). Another part of the explanation lies in the combination of courier services (risk score = 2) and cash-on-delivery: for the full sample (N = 194), there is positive link, significant at the 1% level, between LOGISTICS_COURIER and COD (results not reported).

5.3. Control variables

In 3.2 we announced that we would test whether the degree of offline penetration of a payment instrument positively affects its adoption by e-retailers. As explained in 4.3, we could only do this for payment cards, not for e-money. And for cash-on-delivery such a (direct) test obviously makes no sense. In Table 6 it can be seen that %CARDS_CREDIT_FINDEX has, in line with expectations, a positive and significant impact on the acceptance of credit cards in models 1-5, but not in model 6, and that the impact becomes altogether insignificant when DELIVERY_RISK is added.[xxiv] However, for local payroll cards the impact of consumer uptake of the cards is undeniable. In Table 7, %CARDS_LOCAL has a positive and highly significant coefficient in all models where it appears (7-12).[xxv] As an aside, since the penetration of electronic payment instruments is often linked with the level of economic development of a country, we also experimented with GDP per capita (GDPCAP) and the Human Development Index (HDI) for those payment instruments for which we lacked the necessary data (ANYE) or for which a straightforward test is simply not possible (COD). As can be seen, for e-money this was not particularly successful (Table 8). For COD, we do find some results that make sense: HDI appears with a negative sign in models 4-6 in Table 9, and is significant in two of the three models. Also for

COD, in models not reported here, %ACCOUNT_BANK appeared with a negative sign in models 4-6, but was only significant (at the 5% level) in model 4. %ACCOUNT_FI, for its part, proved insignificant in all models.

Turning to the site-specific control variables, the results for OFFLINE_PRESENCE are both predictable and clear-cut: there is a consistent negative impact on the adoption of the online payment instruments (credit cards and e-money), a consistent positive impact on the acceptance of offline local payroll cards (albeit somewhat less significant), and no impact at all on cash-on-delivery. The latter makes sense because pure-plays can make use of home delivery services that allow customers to pay cash. Finally, our results for the dummies that try to capture whether merchants want to sell to foreign markets also make sense. INTERNAT_CUR, INTERNAT_LNG, and INTERNAT_DELIV have a positive impact on the acceptance of the more international payment instruments (credit cards and e-money), and this across the board (Tables 6 and 8). The results for COD are more mixed: the variables always appear with a negative sign, as expected, but are not always significant (Table 9). The only result that needs some explaining is the negative impact on the acceptance of local payroll cards; for INTERNAT_CUR, that is (Table 8). Indeed, it is not immediately clear why sites with an international orientation would shun what is after all a fairly novel local payment instrument. This said, the explanation is simple: the negative impact of INTERNAT_CUR is caused by the 7 Uzbek websites that we mentioned earlier: these sites sell local handicrafts and are thus not particularly targeting the local market. Once these sites are removed (results not reported), the impact disappears completely, as already mentioned in endnote 19.

6. Conclusions

In this paper, we have described and analysed the adoption of payment instruments by e-retailers in five Central Asian transition economies. To the best of our knowledge, we are the first to establish such a *status quaestionis*. The grand picture that emerged from our descriptive analysis can be summarized as follows. For one, there are wide divergences in the state of the *offline* payments market: the penetration of payment cards differs dramatically across countries, and so does access to financial services. Second, compared to their developed counterparts, e-retailers in the region still rely more on traditional, paper-based payment instruments such as offline bank transfers and COD. Somewhat surprisingly, there did not prove to be a significant (negative) correlation between on the one hand the percentage of banked people or the countries' level of economic advancement (as measured by GDP per capita) and the availability of a cash-on-delivery option on the other, and this neither in the univariate nor in the logit analysis. (There is such a link with the HDI, but not in all models; see Table 9). However, from the perspective of the e-retailers, perhaps the *precise* number of people who do not have a bank account does not matter: as long as the number is substantial, a site leaves a substantial portion of the population in the cold if it does not accept cash. Overall, the situation therefore seems to be one where the majority of the sites in all countries have little choice but to accept at least one paper-based payment instrument (in order to cater for the unbanked), but where on top of that quite a few sites in the more advanced countries (Kazakhstan and Uzbekistan) also accept electronic payment instruments, which is hardly the case in the other three countries.

Where delivery methods are concerned, the most interesting finding is the high number of sites that have set up delivery channels of their own, either private delivery or in-store pick-up. Although the setting is not fully comparable, it is tempting to refer in this respect to the decision by Alibaba Group, China's leading e-commerce company, to build a massive logistics network for its Taobao B2C site. The reason is that Alibaba was dissatisfied with the "delays and patchy quality in distribution and delivery" offered by local logistics companies (Hille, 2010). More recently, 360buy, the group which runs Jingdong Mall, China's second-largest online retailer, made a similar push: over the next three years it is pouring CNY 10 billion into a nationwide logistics and delivery service (Hille, 2012). Apparently, many e-retailers in transition countries where the national postal system is not reliable - and on top of that credit card usage is not widespread – have reached the same conclusion.

Turning to our logit analysis, on the theoretical level we can conclude that the TCM model put forward by Liezenberg et al. (2007) appears relevant. Specifically, our results confirm that higher product risk increases the probability that online merchants adopt lower-risk instruments such as debit cards. Also in line with the TCM model, we find a negative relationship between product risk and the adoption of higher-risk credit cards. However, here we cannot exclude a competing explanation, in the form of acceptance costs for the merchant. We also find that product and delivery risk are interlinked: merchants who offer higher-risk delivery options are also more prone to adopt higher-risk payment instruments.

From an empirical angle, our two core hypotheses – on the role of risk – are broadly supported, although evidence for the first is less strong than for the second, since it proved impossible to disentangle the impacts of risk and cost, except in the rather unique case of payroll cards in Uzbekistan. Our control variables also yield interesting results. For one, we find that pure-plays are more likely to adopt online payment methods, and less likely to adopt offline alternatives – with one exception, namely COD, but this has already been explained. Second, we find that sites that target international markets are more likely to adopt online payment methods, but do not necessarily shun (local) offline substitutes, as most probably also want to cater to the domestic market. Finally, for both credit and (especially) local payroll cards we find evidence that offline penetration positively affects online merchant adoption, in line with the network externalities theory.

In terms of managerial implications, it is interesting to note that at least credit card companies seem well aware of the importance that online merchants attach to payment risk. The 3-D Secure technology is a case in point. 3-D Secure is a protocol that adds a layer of security to online credit (and debit) card transactions by redirecting cardholders to a secure page where they must enter a secure passcode. 3-D Secure was developed by Visa and is marketed as Verified by Visa. MasterCard later also adopted it, under the name SecureCode. 3-D Secure is in fact card companies' second major attempt to make online card transactions safer, their earlier attempt - Secure Electronic Transactions (SET), which was launched in 1996 – having failed to gain acceptance by merchants and cardholders alike. Interestingly, unlike for SET, when they launched 3-D Secure, both Visa and MasterCard offered (eligible) merchants who enrolled in the program a "chargeback liability shift". This implies that the payment risk, R_P, no longer lies with the merchant, but either with the issuing bank (when the merchant is enrolled in 3-D Secure, but the cardholder is not), or with the cardholder (when both the merchant and the issuing bank are enrolled and the password was entered correctly[xxvi]). According to the TCM model, such an incentive should encourage uptake by merchants.

Obviously, our study is not without its limitations. As already alluded to, there is the limited availability and uncertain quality of data on the offline payments market. Second, our proxies for product risk and merchants' risk aversion are fairly rough. Predictably, our first set of suggestions for further research build on this. For one, we would encourage future researchers to rely less on publicly available data, and – in line with what we have done in the present paper for the e-retailers side – try to collect data on the penetration of payment instruments themselves; either by contacting banks and payment providers directly, or by conducting a survey among consumers. Second, a natural extension of our research would be to try to improve the data collection effort on the e-retailers side; for example, by coming up with a better way to gauge average transaction size, either on the sector or on the site level. We also see three wider-ranging avenues for further research. First, it would be interesting to complement our supply-side test of the TCM model with a demand-side test. Second, it would be interesting to compare our findings with findings for developed economies (although the lack of variation in the acceptance of cards might pose problems similar to those that we experienced for COD). Finally, even more interesting would be a longitudinal analysis, in particular with an eye on whether e-commerce practices in transition economies will, over time, converge with those in developed markets or whether transition economies will continue to exhibit idiosyncrasies.

Acknowledgements

We are indebted to our colleague Malaika Brengman for comments on earlier versions of this paper and for her help in scoring the sectors on product risk. We thank Dominique Steenbeek (MasterCard Worldwide) for providing us with information about merchant fees for online credit/debit card payments in Central Asia. We also would like to express our gratitude to several contacts at Kazkommertsbank of Kazakhstan, Central Bank of Kyrgyzstan, National Bank and VneshEconom Bank of Turkmenistan, as well as Hamkor Bank and Asaka Bank of Uzbekistan, for providing additional information on local payment methods.

References

Alzola, L.M. and Robaina, V.P. The Impact of Pre-sale and Post-sale Factors on Online Purchasing Satisfaction: A Survey. *International Journal of Quality & Reliability Management,* 27, 2, 2010, 121-137.

Arango, C. and Taylor, V. Merchant Acceptance, Costs, and Perceptions of Retail Payments: A Canadian Survey. Bank of Canada Discussion Paper 2008-12. (August 2008) Available at <http://www.bankofcanada.ca/2008/08/publications/research/discussion-paper-2008-12/>. Last accessed October 12, 2012.

Avesta Investment Group. A Review of Essential Economic Events: Plastic Card Turnover Consisted of 594 bn Soum. (Обзор Основных Экономических Событий: Оборот по пластиковым картам составил 594 млрд. Сум) (March 10, 2008) Available at <http://data.cbonds.info/comments/2008/30406/ud080310r.pdf>. Last accessed October 12, 2012. Translated from a Russian-language news source.

Basu, A. and Muylle, S. Online Support for Commerce Processes by Web Retailers, *Decision Support Systems*, 34, 4, 2002, 379-395.

Bleyen, V.-A., Van Hove, L. and Hartmann, M. Classifying Payment Instruments: A Matryoshka Approach. *Communications & Strategies,* 79(3rd Quarter), 2010, 73-94.

Demirguc-Kunt, A. and Klapper, L. Measuring Financial Inclusion: The Global Findex Database, World Bank Policy Research Paper 6025, April 2012.

European Bank for Reconstruction and Development (EBRD). The Life in Transition survey II. (June 29, 2011). Available at <http://www.ebrd.com/pages/research/publications/special/transitionII.shtml>. Last accessed October 12, 2012.

Federal Financial Institutions Examination Council (FFIEC). Retail Payment Systems. IT Examination Handbook. (February, 2010). Available at <http://ithandbook.ffiec.gov/ITBooklets/FFIEC_ITBooklet_RetailPaymentSystems.pdf >. Last accessed October 12, 2012.

Fries, S. and Taci, A. Cost Efficiency of Banks in Transition: Evidence from 289 Banks in 15 Post-communist Countries. *Journal of Banking and Finance,* 29, 1, 2005, 55-81.

Gavish, B. & Tucci, C.L. Fraudulent Auctions on the Internet, *Electronic Commerce Research,* 6, 2, 2006, 127-140.

Govers, R. and Go, F.M. Projected Destination Image Online: Website Content Analysis of Pictures and Text. *Information Technology & Tourism,* 7, 2, 2005, 73-89.

Guislain, P. The Postal Sector in Developing and Transition Countries: Contributions to a Reform Agenda*.* The World Bank Group Global Information and Communication Technologies Department, Policy Division. Working Paper. (September 1, 2004). Available at <http://go.worldbank.org/ZU787HHW00>. Last accessed October 12, 2012.

Hayes, A.F. and Krippendorff, K. Answering the Call for a Standard Reliability Measure for Coding Data. *Communication Methods and Measures,* 1, 1, 2007, 77-89.

Hawk, S. A Comparison of B2C E-Commerce in Developing Countries. *Electronic Commerce Research,* 4, 3, 2004, 181-199.

Hille, K. Alibaba Plans China Delivery Network. *Financial Times.* (October 20, 2010). Available at <http://www.ft.com/cms/s/0/8dbb3baa-dc6d-11df-a0b9-00144feabdc0.html#axzz18BiWRE8L>. Last accessed October 12, 2012.

Hille, K. Chinese Online Retailer Eyes Acquisitions. *Financial Times.* (June 13, 2012). Available at <http://www.ft.com/cms/s/0/8e99bf70-b46f-11e1-bb2e-00144feabdc0.html#axzz29GDRd5qD >. Last accessed October 16, 2012.

Hinshaw, D. Online Shopping Emerges in Nigeria. *The Wall Street Journal.* (June 5, 2012). Available at <http://online.wsj.com/article/SB40001424052702303879604577412043390891430.html>. Last accessed October 16, 2012.

ICT Policy Project. Review of Information and Communications Technologies Development in Uzbekistan for 2006 – 2008. UNDP. CIAU. Available at <http://www.undp.uz/en/publications/publication.php?id=212>. Last accessed October 12, 2012.

Innopay, *Online payments 2009 - European market overview*, March. Available at <http://www.innopay.com/node/215>. Last accessed October 12, 2012.

Katz, M.L. and Shapiro, C. Network Externalities, Competition, and Compatibility, *American Economic Review*, 75, 3, 1985, 424-440.

Kosse, A. Creditcards: acceptatie en gebruik van toeslagen door winkeliers. Een pilot onderzoek, working paper, De Nederlandsche Bank, June, 2010.

Koyuncu,C. and Bhattacharya, G. The Impacts of Quickness, Price, Payment Risk, and Delivery Issues on On-line Shopping. *Journal of Socio-Economics,* 33, 2, 2004, 241-251.

Lee, H.L. and Whang, S. Winning the Last Mile of E-Commerce. *MIT Sloan Management Review*, 42, 4, 2001, 54-62.

Li, H., Ward, R. and Zhang, H. Risk, Convenience, Cost and Online Payment Choice: A Study of eBay Transactions. Working paper, Georgia Institute of Technology, 2003. Available at <http://www.prism.gatech.edu/~hl45/research/ebay.pdf>. Last accessed October 12, 2012.

Liezenberg, C., Lycklama, D. and Smorenberg, H. Understanding Buyer and Seller Behaviour for Improved Payment Product Development. *Journal of Payments Strategy & Systems*, 1, 3, 2007, 219-227.

Mascha, M.F., Miller, C.L. & Janvrin, D.J. The Effect of Encryption on Internet Purchase Intent in Multiple Vendor and Product Risk Settings. *Electronic Commerce Research,* 11, 4, 2011, 401-419.

Mayhew, B. *Central Asia (Lonely Planet Travel Guides).* Fourth Edition. Lonely Planet, 2007.

Milne, R. A Swedish Take on 'Buy Now, Pay Later'. *Financial Times.* (March 6, 2013). Available at <http://www.ft.com/cms/s/0/35f1d24a-7f6c-11e2-8d96-00144feabdc0.html#axzz2S7kXjNkJ>. Last accessed May 2, 2013.

Molla, A. and Licker, P.S. eCommerce Adoption in Developing Countries: A Model and Instrument. *Information & Management,* 42, 6, 2005, 877-899.

Muylle, S. and Basu, A. Online Support for Commerce Processes and Survivability of Web Retailers, *Decision Support Systems*, 38, 1, 2004, 101-113.

Money News. The Volume of Non-cash Payments is Rising in Uzbekistan. (В Узбекистане растут объемы безналичных карточных платежей.) (February 1, 2007). Available at <http://moneynews.ru/7786/>. Last accessed October 12, 2012. Translated from a Russian language news source.

National Bank of the Republic of Kazakhstan. Statistics Regarding Plastic Cards. (Статистика по платежным карточкам). (November 1, 2010). Available at <http://www.nationalbank.kz>. Last accessed October 12, 2012. Translated from a Russian language bank source.

National Bank of the Kyrgyz Republic. Report on Current Payment System of Kyrgyz Republic. Отчет о текущем состоянии платежной системы Кыргызской Республики. (May 27, 2010). Available at <http://www.nbkr.kg/index1.jsp?item=97&lang=RUS>. Last accessed October 12, 2012. Translated from a Russian language bank source.

National Bank of Tajikistan. Payment System of Tajikistan. Платежная система Республики Таджикистан. (May, 2010). Available at <http://nbt.tj/ru/pl_sys/>. Last accessed October 12, 2012. Translated from a Russian language bank source.

National Bank for Foreign Economic Activity of the Republic of Uzbekistan. Plastic Cards of NBU – For Those Who Value Time and Comfort! (Пластиковые карточки НБУ - для тех, кто ценит время и комфорт!). (2010). Available at <http://uzbank.net/plastfiznbu.php>. Last accessed October 22, 2012. Translated from a Russian language bank source.

Odedra-Straub, M. E-commerce and Development: Whose Development? *Electronic Journal of Information Systems in Developing Countries,* 11, 2, 2003, 1-5.

Plus Journal. Plastic Card Market of Uzbekistan. (Карточный рынок Узбекистана: 75:25 в пользу торговых транзакций) (February 28, 2010). Available at

<http://www.plusworld.ru/our_region/page1_9645.php>. Last accessed October 12, 2012. Translated from a Russian language news source.

Polasik, M. and Fiszeder, P. Factors Determining the Acceptance of Payment Methods by Online Shops in Poland. Working paper (February 28, 2010). Nicolaus Copernicus University, Torun, Poland. Available at <http://ssrn.com/abstract=1541202>. Last accessed May 2, 2013.

Ramanathan, R. E-commerce Success Criteria: Determining Which Criteria Count Most. *Electronic Commerce Research,* 10, 2, 2010, 191-208.

Roztocki, N. and Weistroffer, H.R. Information Technology Investments in Emerging Economies. *Information Technology for Development,* 14, 1, 2008, 1-10.

Roztocki, N. and Weistroffer, H.R. Research Trends in Information and Communications Technology in Developing, Emerging and Transition Economies. *Roczniki Kolegium Analiz Ekonomicznych Zeszyt (Annals of the Collegium of Economic Analysis)*, 20, 2009, 113-128. Available at <http://ssrn.com/abstract=1577270>. Last accessed October 12, 2012.

Singh, M. E-services and Their Role in B2C E-commerce. *Managing Service Quality,* 12, 6, 2002, 434-446.

Stroborn, K., Heitmann, A., Leibold, K. and Frank, G. Internet Payments in Germany: A Classificatory Framework and Empirical Evidence. *Journal of Business Research,* 57, 12, 2004, 1431– 1437.

Trend Capital. Turnover of plastic cards in Uzbekistan has increased 2,5 times in the first half of the year. (Оборот по пластиковым картам в Узбекистане в первом полугодии вырос в 2,5 раза) (July 28, 2010). Available at <http://mail2.trend.az/capital/banks/1727341.html>. Last accessed October 12, 2012. Translated from a Russian language news source.

UNDP. The Human Development Index (HDI). (2010). Available at <http://hdr.undp.org/en/media/HDR_2010_EN_Table1_reprint.pdf>. Last accessed October 12, 2012.

Van Bossuyt, M. and Van Hove, L. Mobile Payment Models and Their Implications for NextGen MSPs. *info - The Journal of Policy, Regulation and Strategy*, Special Issue on “The Redesign of Mobile Business”, 9, 5, 2007, 31-43.

Van Hove, L. Electronic Money and the Network Externalities Theory: Lessons for Real Life, *Netnomics*, 1, 2, 1999, 137-171.

Van Hove, L. Could 'Nudges' Steer Us Towards a 'Less-Cash Society'? Working paper, Vrije Universiteit Brussel (Free University of Brussels), September 16, 2009. Available at Available at <http://ssrn.com/abstract=1317360>. Last accessed October 12, 2012.

World Bank. Population 2009. Data Catalog (2010). Available at <http://data.worldbank.org/data-catalog>. Last accessed October 12, 2012.

Zhang, H. and Li, H. Factors Affecting Payment Choices in Online Auctions: A Study of eBay Traders, *Decision Support Systems*, 42, 2, 2006, 1076-1088.

APPENDIX

Table A1. Definitions of explanatory variables

Variable codes	Description	Source
Site-specific variables		
OFFLINE_PRESENCE	Dummy variable: bricks & clicks = 1, pure-plays = 0.	Own survey.
INTERNAT_CUR	Dummy variable: takes 1 when prices are (also) mentioned in foreign currency, 0 otherwise.	Own survey.
INTERNAT_LNG	Dummy variable: takes 1 when website content is (also) in foreign language, 0 otherwise.	Own survey.
INTERNAT_DELIV	Dummy variable: takes 1 when the site states explicitly that they deliver internationally, 0 otherwise.	Own survey.
LOGISTICS_PRIVATE	Dummy variable for delivery type: private delivery 0/1.	Own survey.
LOGISTICS_COURIER	Dummy variable for delivery type: courier service 0/1.	Own survey.
LOGISTICS_INSTORE	Dummy variable for delivery type: in-store pick-up 0/1.	Own survey.
DELIVERY_RISK	Ordinal variable, ranges between 1 and 3. Merchants are assigned a 'risk coefficient' corresponding to the highest-risk delivery method that they use, with in-store pick-up and private delivery low-risk (value = 1), courier services medium-risk (value = 2), and the national postal system high-risk (value = 3).	Own survey.
Sector-specific variables		
PRODUCT_RISK	E-commerce sectors have been categorized according to the average value of the products sold: Low (value = 1) *versus* Medium or High (2).	Own survey.
Country-specific variables		
%ACCOUNT_BANK	Percentage of households with a bank account, for the year 2010	EBRD (2011).
%ACCOUNT_FI	Percentage of individuals aged 15+ with an account at a formal financial institution, for the year 2011	Demirguc-Kunt and Klapper (2012).
%CARDS_INTERNAT	Number of payment cards with international brands (Visa, MasterCard, etc.) in circulation divided by total population * 100. There are no such cards in Tajikistan and Turkmenistan, so these countries are excluded from the analysis.	Authors' own compilation based on National Banks. See Table 2.
%CARDS_LOCAL	Number of local debit cards in circulation divided by total population * 100. Includes only Kazakhstan and Uzbekistan.	Authors' own compilation based on National Banks. See Table 2.
%CARDS_CREDIT_LITS	Percentage of households with a credit card, for the year 2010	EBRD (2011).
%CARDS_DEBIT_LITS	Percentage of households with a debit card, for the year 2010	EBRD (2011).
%CARDS_CREDIT_FINDEX	Percentage of individuals aged 15+ with a credit card, for the year 2011	Demirguc-Kunt and Klapper (2012).
%CARDS_DEBIT_FINDEX	Percentage of individuals aged 15+ with a debit card, for the year 2011	Demirguc-Kunt and Klapper (2012).
GDPCAP	Gross Domestic Product per capita, in USD, for the year 2009	World Bank (2010). See Table 2.
HDI	Human Development Index, for the year 2009 (range: 0.58-0.71)	UNDP (2010).
TRANSACTCAP	Number of transactions with payment cards, per capita	Authors' own compilation based on National Banks. See Table 2.

Table A2. Descriptive Statistics

	N	Mean	Std. Deviation	Skewness	
	Statistic	Statistic	Statistic	Statistic	Std. Error
Site-specific variables					
OFFLINE_PRESENCE	194	.58	.50	-.32	.18
INTERNAT_CUR	194	.14	.35	2.10	.18
INTERNAT_LNG	194	.12	.33	2.3	.18
INTERNAT_DELIV	194	.07	.26	3.33	.18
LOGISTICS_PRIVATE	194	.19	.39	1.59	.18
LOGISTICS_COURIER	194	.63	.48	-.56	.18
LOGISTICS_INSTORE	194	.31	.47	.81	.18
DELIVERY_RISK	194	1.81	.67	.24	.18
Sector-specific variables					
PRODUCT_RISK	194	1.73	.44	-1.06	.18
Country-specific variables					
%ACCOUNT_BANK	191	7.26	4.39	-.70	.17
%ACCOUNT_FI	194	32.11	14.69	-1.10	.18
%CARDS_INTERNAT	185	34.61	21.97	-.79	.18
%CARDS_LOCAL	162	6.34	9.92	1.35	.19
%CARDS_CREDIT_LITS	191	4.16	2.43	-.68	.18
%CARDS_DEBIT_LITS	191	5.65	2.59	-1.31	.18
%CARDS_CREDIT_FINDEX	194	6.55	3.40	-.74	.18
%CARDS_DEBIT_FINDEX	194	24.14	10.80	-1.33	.18
GDPCAP	194	4865.77	2759.65	-.67	.18
HDI	194	.68	.05	-.74	.18
TRANSACTCAP	191	5.96	3.91	-.68	.18

Table A3a. Correlations (N = 194, except indicated otherwise)

	OFFLINE_PRESENCE	INTERNAT_CUR	INTERNAT_LNG	INTERNAT_DELIV	LOGISTICS_PRIVATE	LOGISTICS_COURIER	LOGISTICS_INSTORE	DELIVERY_RISK	PRODUCT_RISK	%ACCOUNT_BANK (N=191)	%ACCOUNT_FI	%CARDS_INTERNAT (N=185)	%CARDS_LOCAL (N=162)	%CARDS_CREDIT_LiTS (N=191)	%CARDS_DEBIT_LiTS (N=191)	%CARDS_CREDIT_FINDEX	%CARDS_DEBIT_FINDEX	GDPCAP	HDI	TRANSACTCAP (N=191)
OFFLINE_PRESENCE	1																			
INTERNAT_CUR	-.168** .019	1																		
INTERNAT_LNG	-.027 .707	.120* .095	1																	
INTERNAT_DELIV	-.003 .963	.176** .014	.258*** .000	1																
LOGISTICS_PRIVATE	-.010 .894	-.044 .546	.057 .432	-.085 .240	1															
LOGISTICS_COURIER	.021 .767	-.035 .632	-.072 .318	.171** .017	-.557*** .000	1														
LOGISTICS_INSTORE	.535*** .000	-.048 .508	-.052 .470	-.060 .405	-.074 .302	.261*** .000	1													
DELIVERY_RISK	.028 .701	-.044 .541	-.083 .251	.255*** .000	-.433*** .000	.779*** .000	.187*** .009	1												
PRODUCT_RISK	.095 .189	-.194*** .007	-.232*** .001	-.101 .161	-.151** .036	.120* .095	.134* .062	.093 .198	1											
%ACCOUNT_BANK (N=191)	.010 .887	-.300*** .000	-.135* .063	.082 .261	-.170** .019	.294*** .000	.045 .541	.405*** .000	.065 .370	1										
%ACCOUNT_FI	-.002 .979	-.281*** .000	-.118 .100	.111 .125	-.099 .171	.228*** .001	.078 .279	.345*** .000	.052 .469	.947*** .000	1									
%CARDS_INTERNAT (N=185)	.024 .742	-.282*** .000	-.118 .110	.066 .370	-.188** .010	.302*** .000	.041 .578	.407*** .000	.068 .358	.999*** .000	.930*** .000	1								
%CARDS_LOCAL (N=162)	-.073 .354	.359*** .000	.174** .027	-.006 .941	.231*** .003	-.330*** .000	.056 .481	-.397*** .000	-.141* .074	-1.00*** .000	-1.00*** 0.000	-1.00*** 0.000	1							
%CARDS_CREDIT_LiTS (N=191)	.017 .815	-.307*** .000	-.139* .055	.075 .301	-.179** .013	.302*** .000	.036 .624	.411*** .000	.073 .313	.997*** .000	.921*** .000	1.00*** 0.000	-1.00*** 0.000	1						
%CARDS_DEBIT_LiTS (N=191)	-.027 .713	-.227*** .002	-.092 .207	.109 .133	-.106 .143	.225*** .002	.092 .205	.334*** .000	.011 .876	.920*** .000	.997*** .000	.896*** .000	-1.00*** .000	.889*** .000	1					
%CARDS_CREDIT_FINDEX	.016 .824	-.316*** .000	-.140* .052	.096 .185	-.137* .057	.269*** .000	.054 .458	.387*** .000	.078 .281	.995*** .000	.975*** .000	.989*** .000	-1.00*** .000	.985*** .000	.954*** .000	1				
%CARDS_DEBIT_FINDEX	-.012 .870	-.253*** .000	-.102 .155	.116 .106	-.077 .285	.202*** .005	.091 .207	.316*** .000	.036 .616	.901*** .000	.993*** .000	.873*** .000	-1.00*** .000	.868*** .000	.999*** .000	.943*** .000	1			
GDPCAP	.017 .819	-.306*** .000	-.140* .051	.080 .270	-.172** .017	.296*** .000	.038 .603	.408*** .000	.075 .300	.999*** .000	.909*** .000	1.00*** 0.000	-1.00*** .000	.999*** .000	.903*** .000	.971*** .000	.859*** .000	1		
HDI	.006 .929	-.297*** .000	-.136* .058	.087 .230	-.160** .026	.285*** .000	.047 .520	.398*** .000	.063 .380	.997*** .000	.930*** .000	.997*** .000	-1.00*** 0.000	.989*** .000	.938*** .000	.973*** .000	.890*** .000	.994*** .000	1	
TRANSACTCAP (N=191)	.017 .811	-.314*** .000	-.144** .047	.075 .304	-.179** .013	.302*** .000	.032 .656	.412*** .000	.076 .295	.997*** .000	.919*** .000	.999*** .000	-1.00*** .000	.999*** .000	.886*** .000	.984*** .000	.865*** .000	.999*** .000	.991*** .000	1

Note: Pearson correlation (2 tailed); *, **, *** indicate significance levels of 10%, 5%, and 1% respectively.

Table A3b. Country-level correlations (N = ****, except indicated otherwise)

		%ACCOUNT_BANK	%ACCOUNT_FI	%CARDS_INTERNAT	%CARDS_LOCAL	%CARDS_CREDIT_LiTS	%CARDS_DEBIT_LiTS	%CARDS_CREDIT_FINDEX	%CARDS_DEBIT_FINDEX	GDPCAP	HDI	TRANSACTCAP
%ACCOUNT_BANK	r	1										
	N	4										
%ACCOUNT_FI	r	.92*	1									
	Sig.	.084										
	N	4	5									
%CARDS_INTERNAT	r	.997**	.883	1								
	Sig.	.048	.311									
	N	3	3	3								
%CARDS_LOCAL	r	-1.00***	-1.00***	-1.00***	1							
	Sig.											
	N	2	2	2	2							
%CARDS_CREDIT_LiTS	r	.992***	.860	1.00**	-1.00***	1						
	Sig.	.008	.140	.012								
	N	4	4	3	2	4						
%CARDS_DEBIT_LiTS	r	.884	.997***	.838	-1.00***	.821	1					
	Sig.	.116	.003	.367		.179						
	N	4	4	3	2	4	4					
%CARDS_CREDIT_FINDEX	r	.990**	.970***	.979	-1.00***	.965**	.941*	1				
	Sig.	.010	.006	.132		.035	.059					
	N	4	5	3	2	4	4	5				
%CARDS_DEBIT_FINDEX	r	.865	.995***	.810	-1.00***	.798	.999***	.941**	1			
	Sig.	.135	.000	.399		.202	.001	.017				
	N	4	5	3	2	4	4	5	5			
GDPCAP	r	.998***	.662	1.00***	-1.00***	.995***	.861	.750	.616	1		
	Sig.	.002	.223	.008		.005	.139	.145	.268			
	N	4	5	3	2	4	4	5	5	5		
HDI	r	.984**	.647	.993*	-1.00***	.958**	.926*	.696	.615	.979***	1	
	Sig.	.016	.238	.075		.042	.074	.192	.269	.004		
	N	4	5	3	2	4	4	5	5	5	5	
TRANSACTCAP	r	.994***	.873	.999**	-1.00***	.996***	.834	.971**	.811	.999***	.975**	1
	Sig.	.006	.127	.030		.004	.166	.029	.189	.001	.025	
	N	4	4	3	2	4	4	4	4	4	4	4

Note: Pearson correlation (2 tailed); *, **, *** indicate significance levels of 10%, 5%, and 1% respectively.

Table A4. List of e-commerce sectors and their classification in terms of product risk

Low risk	Medium risk	High risk
Books / Music / Videos	Apparel / Accessories	Automotive Parts / Accessories
Flowers / Gifts	Home Furnishings	Computers / Electronics
Food / Drug	Mass Merchant	Hardware / Home Improvement
Health / Beauty	Office Supplies	Housewares
	Sporting Goods	Jewelry
	Toys / Hobbies	Specialty / Non-apparel

[i] Transition economies can be defined as "economies that are in transition from a communist style central planning system to a free market system" (Roztocki & Weistroffer, 2008b, p. 2).
[ii] Note that in the published version of the Li et al. paper – Zhang & Li (2006) – the theoretical model is no longer there.
[iii] From a consumer perspective, this could be called vendor risk (Mascha et al., 2011, p. 405).
[iv] See Figure 3 in Liezenberg (2007, p. 222) for a schematic presentation of the model.
[v] Where r_l is concerned, this statement is qualified below.
[vi] In their experiment, Mascha et al. (2011) use product price as the mechanism for manipulating product risk.
[vii] As multiple answers were possible, this need not equate with 3 out of 5.
[viii] It goes without saying that this can be mutually beneficial for both seller and buyer, as anecdotal evidence for Nigeria shows: "Millions of people in [Lagos] are prospering and many are shopping online for the first time. But in a country that has become synonymous with online fraud, they would sooner hand money to a courier than enter their credit-card numbers on a website. So online shopping site DealDey.com employs of fleet of motorcyclists to dart through gridlocked streets to meet online shoppers waiting to pay for their purchases with cash" (Hinshaw, 2012).
[ix] Kz=12.8% and Uz=44.4%, compared to Kg=4.3%; χ^2-test p<.000.
[x] The classification of PayPal as 'e-money' can be criticized, as the current version of PayPal is mainly used not as an electronic wallet but rather as a way for small merchants to indirectly accept credit cards. However, we specifically did not want to lump PayPal together with the straightforward acceptance of credit cards.
[xi] Kz=28.6% and Uz=36.1% vs. Kg=8,7%; χ^2-test p=.065.
[xii] See http://www.internetretailer.com/top500/list/
[xiii] Against better judgment, after the facts we did send out an e-mail survey – in order to, at the very least, be able to check whether our ratings made sense. Unfortunately, we only received six complete responses out of a total of 181 surveys sent. Of these six responses, five were consistent with our coding and one was not.
[xiv] As robustness checks, we repeated the regressions in Table 6 for a sample that progressively excluded Turkmenistan (N=191), Tajikistan (N = 185), and Kyrgyzstan (N = 162). This was motivated by the observation that, respectively, none, none, and only one of the websites in these countries offer a credit card payment option. Reassuringly, none of the results disappeared and in several cases the significance levels even improved. As mentioned in 4.3, we also tried a variant of our PRODUCT_RISK variable with three rather than two categories. Again, the product-risk variable has a significant negative impact in all models, be it that the significance drops to the 5% level in models 3 and 9.
[xv] The same is true for offline bank transfers (N = 194); results not reported.
[xvi] We should also point out that if PRODUCT_RISK is replaced by its variant with three instead of two categories, the variable only remains significant (at the 10% level) in models 9 and 12. In all other models, the positive sign remains, but significance hovers just above 10%.
[xvii] Two Uzbek online merchants whom we contacted mentioned 3.5% and 3.6%, respectively.
[xviii] The fact that merchants and commercial banks in certain of the countries pointed out that cardholders pay part of these fees - and in some cases apparently even the entire fee – does not solve our problem.
[xix] There are no fees for cardholders either. Banks only charge companies 1-2% for transferring the salaries of employees to their debit cards.
[xx] Uzbek holders of MasterCard and Visa credit cards need a USD account.
[xxi] Removal of these 7 sites from models 1-6 in Table 7 does not fundamentally alter the results. In fact, the only change is that none of the variables that try to capture the international orientation of a site (INTERNAT_CUR, INTERNAT_LNG, and INTERNAT_DELIV) remain significant, but this is only normal. As an aside, given that adopting credit cards is apparently not an option for many Uzbek e-retailers, in an additional robustness check we also re-estimated the regressions for ANYC (in Table 6) without Uzbekistan (N = 158; results not reported). This leaves unchanged our fundamental results; that is, those for PRODUCT_RISK and DELIVERY_RISK – be it that there are drops in the significance levels. PRODUCT_RISK is now only significant at the 5% level (and only at the 10% level in model 2; that is, the P-value is 0.051). The significance of DELIVERY_RISK drops to 5% in model 9, but stays at the 1% level in models 7-8. This said, the significant results for OFFLINE_PRESENCE disappear completely and those for the INTERNAT variables are severely reduced in number.
[xxii] Note that for Uzbek e-tailers who are not allowed to accept credit cards, the choice is limited to debit cards (mostly payroll cards), e-money, and COD. As explained in 3.1, for all these instruments the payment risk for the seller is low. However, compared to COD payroll cards (and e-money) have the benefit of a lower agreement risk.
[xxiii] In Muylle and Basu (2004, p. 108; italics added), they explain the result as follows: "the fact that prevalent online

payment mechanisms such as credit cards are more attractive for larger payment sums, *due to the associated transaction costs*, may also explain the adoption of such instruments by Web retailers offering expensive products". This obviously clashes with our arguments above.

[xxiv] When %CARDS_CREDIT_FINDEX is replaced by either %CARDS_CREDIT_LITS, %CARDS_INTERNAT, or TRANSACTCAP, the variable only remains significant in the simple models 1-2. But then both %CARDS_INTERNAT and TRANSACTCAP are very rough proxies of the penetration of credit cards. As explained in Section 2, in reality not all international cards are credit cards. Conversely, when %CARDS_CREDIT_FINDEX is replaced by %ACCOUNT_FI, the results improve: %ACCOUNT_FI has a positive and significant coefficient in models 1-7, and the significance levels are higher. Notice that %CARDS_CREDIT_FINDEX and %ACCOUNT_FI are strongly correlated (0.975), which is understandable.

[xxv] When we replaced %CARDS_LOCAL with %CARDS_DEBIT_LITS, the latter proved to be equally significant but – puzzlingly - appeared with a *negative* sign. The same was true for %CARDS_DEBIT_FINDEX. The explanation is that whereas %CARDS_LOCAL focuses on payroll cards, for both %CARDS_DEBIT_LITS and %CARDS_DEBIT_FINDEX a debit card is a debit card. As can be seen in Table A3b, the correlation between %CARDS_DEBIT_LITS and %CARDS_DEBIT_FINDEX is near perfect, but the correlation between either of these and %CARDS_LOCAL is low. In other words, they simply do not measure the same phenomenon. The fact that %CARDS_DEBIT_LITS and %CARDS_DEBIT_FINDEX failed to yield results in regressions (not reported) for ANY(D1+D2) – which measures whether an online vendor accepts Visa Election and/or Maestro cards – confirms that these variables are just not specific enough for our purposes.

[xxvi] When the password is not entered correctly, the transaction is declined.