

Global Research Unit Working Paper #2017-016

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Uncertainty and sequential outward foreign direct investment

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Abstract: This paper studies firms' choice of sequential outward foreign direct investment (OFDI) under uncertainty. Using an illustrative theoretical model where an investor chooses an irreversible OFDI project that maximizes the returns over finite investment periods, we demonstrate that, due to uncertainty, sequential OFDI that accumulates experiential information is advantageous over other types of OFDI in optimizing investment decision. Using Chinese firm-level data and various regression specifications, we find that Chinese firms are more likely to carry out sequential OFDI when the level of uncertainty is high. Macroeconomic uncertainty and investment risk in host countries are found to associate with higher probability of sequential OFDI. Chinese government support policies make firms rely less on sequential OFDI to deal with investment risk. Analyses on different firm types, namely state-owned enterprises (SOEs), foreign invested enterprises (FIEs), and private enterprises (PVEs), each of which has different sensitivity toward investment uncertainty, suggest that more risk-sensitive firm type weighs more on uncertainty, and therefore is prone to choose sequential OFDI. Our results are robust to various definitions of sequential OFDI.

JEL: F21, F23

Keywords: Uncertainty, sequential outward FDI

Acknowledgments: We thank Mingming Jiang, Hong Ma, Madhusudan Mohanty, Feng Zhu and participants of the Second International Conference on the Chinese Economy: Past, Present and Future, and seminar participants at BIS, Shandong University, Tsinghua, UNC Chapel Hill for their helpful comments and suggestions. We are grateful to Shu Yu for sharing data. Faculty research funds of SUNY Buffalo State and National Science Foundation of China (71473150) are gratefully acknowledged. All errors are ours.

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1. Introduction

To establish a foreign direct investment (FDI) project overseas, a multinational firm generally makes two sequential decisions: (1) whether to invest immediately or delay to later periods, and (2) where to place the committed FDI project once decided to invest immediately. Due to the (partial) irreversibility of FDI project (costly if liquidized prematurely), uncertainty creates the value of “forfeit and wait” against undertaking a possibly costly investment in an uncertain environment (Bernanke, 1983; Bloom et al, 2007; Dixit and Pindyck, 1994). Postponing to later periods as opposed to immediate investment decision will be justified if the marginal benefit of “forfeit and wait” outweighs the marginal product satisfying for an investment. Otherwise, the firm moves on to investment immediately, and the FDI location is chosen where the project pays the maximal net present value (NPV) of future returns among numerous possible locations (Bernanke, 1983).

Although the value of “forfeit and wait” and the optimal timing of an irreversible investment when facing uncertainty has been extensively discussed in economics literature (Bloom et al, 2007; Dixit and Pindyck, 1994; Kogut, 1991; Leahy and Whited, 1996; McDonald and Siegel, 1986), little has been studied on, once opting out “forfeit and wait,” how the locational choice is made when facing perceived uncertainty, particularly the choice between accumulating at the location that has prior investment or dispersing to other markets. This is particularly important for outward foreign direct investment (OFDI) as it may encounter more uncertainty and risks (e.g. political risk and foreign market risk) relative to domestic investments.

In this study, we attempt to contribute to this green field by proposing a simple theoretical model that highlights the nexus among uncertainty, information, and the locational choice of OFDI in experienced markets versus new markets. Following Dixit and Pindyck (1994), we label an OFDI in experienced markets as sequential OFDI¹, which can be defined as subsequent OFDI built upon existing OFDI projects in the same or similar market. Subsequently, we categorize OFDI into two broad types: sequential OFDI and non-sequential OFDI. The former possesses prior operational experience in a foreign market that is not available for the latter, hence allowing the firm to accumulate more heuristic knowledge and information about the foreign market than

¹It is akin to stage investment in the sense that, as Dixit and Pindyck (1994) state, the key characteristic of sequential investment is the ability to temporarily or permanently stop investing if the value of the completed project falls or if the expected cost of completing the investment rises.

the latter. Thus, compared to non-sequential OFDI, sequential OFDI is a more cautious and less risky type of OFDI. Based on the intuition that knowledge and information reduce uncertainty², we postulate that, relative to non-sequential OFDI, firms tend to establish sequential OFDI when facing increasing uncertainty.

We utilize Bernanke (1983) recursive theoretical framework to prove our postulation but departing from the main route of Bernanke model that focuses on evaluating the “option value” of “forfeit and wait” associated with irreversibility and uncertainty. Rather, our focal point is on the theoretical channel through which experiential knowledge and information reduce uncertainty and its further influence on the optimal choice of OFDI location. Suppose that, at current period, a firm decides to commit OFDI, the next step is to choose the location of OFDI project by following either sequential or non-sequential FDI strategy, whichever maximizes the expected NPV of future returns. Due to uncertainty, when new information arrives in the next period, the chosen optimal project may turn out to be non-optimal. This is because the sum of current period return (it is realized and known for the firm in the next period) and the NPV of future returns of the committed OFDI estimated with new information may be lower than the NPV of returns of another OFDI project. That project was a non-optimal project in the current period, but it is forecasted to be optimal in the second period when new information becomes known.

Given that OFDI is reversible, the firm would liquidize the committed FDI in the next period and would invest in the other project that yields highest returns. However, irreversibility prevents the firm to do so and motivates it to improve the forecast of future returns to ensure the committed OFDI to be optimal throughout the investment periods. Theoretically, even the forecasted returns of the committed project in the second period is less than the other one (the predicted new optimal project with new information in the second period), the shortfall of committed OFDI to the new optimal project not exceeding the realized return in the current period is sufficient to keep the committed project remaining optimal. Because the new optimal project was forfeited, it did not yield any return in the current period. In other words, the original decision is good as long as the realized return in current period is large enough to cover the possible forecast errors in the second period.

²In Appendix C, we interpret the mechanism that increased information smooths uncertainty via Bayesian Updating.

If we understand this situation from the perspective of the Value at Risk (*VaR*) theory, the realized return in current period is analog to the *VaR*—the worst possible forecast error could occur in order to maintain the committed project optimal. Thus, with given statistical confidence level, minimizing the volatility of forecasting error that arises from uncertainty in foreign markets allows the firm to maximize the chance to retain the committed project optimal throughout investment periods.

Increased knowledge of a foreign market reduces both the cost and uncertainty of operating in a foreign market (Buckley and Casson, 1981; Dixit, 1989; Pindyck, 1988). FDI experience creates (sometime unique) increased market knowledge and information, and uncertain reduction. Eclectic theory of international production (Dunning 1981; 1988) considers experience an owner-specific advantage that promotes FDI. Nourished from operational experience of previous OFDI, sequential OFDI possesses asymmetrically more knowledge and information that reduces uncertainty than non-sequential OFDI. Thus, the model implies that, under uncertain environment, sequential FDI is more desirable for firms to keep the committed project optimal throughout the investment periods.

We then empirically test the theoretical model implication by examining how uncertainty factors affect firms' choice of sequential OFDI using various econometric specifications. Higher uncertainty is expected to lead firms to choose sequential OFDI. Firm-level Chinese OFDI data are used for our empirical study. Chinese OFDI data are advantageous for this study, in that, first, Chinese OFDI is usually trade-related horizontal OFDI that is intended to explore foreign markets. Horizontal OFDI usually targets a specific foreign market, allowing us to better study the uncertainty effect to the locational choice of OFDI; second, although we observed astonishing OFDI from China in recent years, Chinese OFDI is a recent phenomenon starting from the early 1990s. Many of Chinese OFDIs are infant OFDIs without any prior experience. This makes Chinese OFDIs ideal for studying how experiential knowledge and information influence their choice of OFDI under uncertainty.

Our empirical exercises study firms' decision for sequential OFDI from three different perspectives. First, assuming that firms choose either sequential OFDI or otherwise (including both non-sequential OFDI and "forfeit and wait") to be placed in one of 128 possible country

locations³, we use conditional logit method that analyzes the probability of dichotomous choice to estimate how uncertainty factors affect the probability that a firm chooses sequential OFDI. Second, we consider that a firm first decides either to commit investment or “forfeit and wait”; once the firm decides to commit, it chooses sequential or non-sequential OFDI, whichever pays better returns. Thus, a multinomial logit regression method is used to identify what factors affect the probability of choosing sequential or non-sequential OFDI relative to “forfeit and wait.” Finally, we use the nested logit regression (Greene, 2002) to relax the assumption of independence fo irrelevant alternatives (IIA) that is used in both conditional logit and multinomial logit approach. In nested logit approach, alternatives are separated into several groups. It allows the variance to differ across the groups while maintaining the IIA assumption within each group.

Further, we separate data into three subsamples according to their firm types, namely state-owned enterprises (SOEs), foreign-invested enterprises (FIEs), and private enterprises (PVEs), which are perceived to have different sensitivity to risk or uncertainty. We thus repeat the conditional logit regression specification to study the heterogeneous investment behaviors across three firm types when they face uncertainty.

Literature usually refers sequential OFDI as the subsequent investment in the same market where the firm has prior FDI. We extend this definition by considering subsequent OFDI to a country that has similar market structure as the one having firm’s prior OFDI to be sequential OFDI as well. Similar markets are defined from three different perspectives: (1) countries in similar income level according to World Bank categorization; (2) in line with gravity model, we define countries at the same income level and located in the same continent as similar markets; and (3) countries sharing the same culture block categorized in Ronen and Shenkar (1985). Different definitions and measurement of sequential OFDI may render robust empirical results.

To anticipate our empirical findings, we find evidence that high uncertainty, including macroeconomic uncertainty and investment risk in host countries, increases the occurrence of sequential OFDI. For instance, 1% increase in inflation (macroeconomic uncertainty) is associated with about 0.07 percent more chances that a firm establishes sequential OFDI. Chinese government support policies (GSP) help mitigate foreign market uncertainty. On one

³We selected 128 countries due to data availability.

hand, it is found to promote overall Chinese OFDI, including both sequential and non-sequential OFDI. On the other hand, it reduces the impact of investment risk to sequential OFDI, making sequential OFDI less important. Overall, in accordance to our theory proposition, empirical results suggest that while facing increasing uncertainty, firms tend to choose cautious sequential OFDI. For robustness, we further explore the heterogeneity across firm types. For three firm types, SOE, FIE, and PVE, that are inherently different in sensitivity to uncertainty, we find that PVE is most likely to choose sequential OFDI in reacting to increased uncertainty. While SOEs are sensitive to foreign market uncertainty, they are numb to Chinese government support. Interestingly, neither uncertainty in host countries nor government support from China has impact on FIV decision on sequential OFDI.

Three aspects contribute to FDI literature in this study: First, it offers an illustrative theory model that integrates a recursive macroeconomic model and *VaR* finance theory to identify a possible channel that information and uncertainty affects OFDI decision. Second, we extend the definition of sequential OFDI. Subsequent OFDIs that are placed in either same or similar markets are defined as sequential OFDIs. Similar markets are defined according to three different standards, namely income level, income level and geographic proximity, and culture blocks. Finally, we explore various ways that a firm could possibly make investment decision, then empirically investigate them via appropriate regression specifications, thereby showing the robustness of our empirical results.

The paper proceeds as follows. The following section details the theoretical model that demonstrates how knowledge and information associated with sequential OFDI reduces uncertainty, hence increasing the chance of firm's optimal OFDI decision. In Section 3, we offer some stylized facts about Chinese OFDI. We then undertake rigorous empirical analysis in Section 4 to study how uncertainty affects firms to choose sequential OFDI. Section 5 concludes the paper.

2. An illustrative theoretical model

In this section, we use a theoretical model to demonstrate a theoretic mechanism via which a firm decides to choose a sequential OFDI or a non-sequential OFDI among irreversible alternatives under stochastic conditions. To reduce uncertainty, a firm can either analyze publicly

available information or actively learn and accumulate knowledge of local market through a prior OFDI experience.

Following Bernanke (1983), our model assumes that: First, an OFDI project is economically irreversible putty-clay project that could not be liquidized without substantial cost. Second, investors can choose an OFDI project in different markets, but projects are mutually exclusive alternatives due to limited resources and time for multiple projects simultaneously. Third, the firm is risk neutral, and there is no insurance to cover the failure of OFDI.

Under these assumptions, a firm decides which market to invest by assessing the NPV of returns of an OFDI project in finite investment periods. The return of investment in future periods are subject to uncertainty and need the firm to make forecast according to the information it possesses.

2.1. The model setup and derivation

We consider a firm that decides to either choose at most one of k markets to invest its OFDI (Once decided, the OFDI project is irreversible) or defer the commitment to the next period in order to gather more information that helps to better assess the future return of the project. By deferring the investment, the firm also forfeits the investment return of the current period.

For simplicity, we denote the current period as s , and the finite investment period ends in T , where $s = t, t+1, \dots, T$. The available information set at period s is I_s . Following Bernanke (1983), we let the number of information set be finite and take I_s to be an $n_s \times 1$ vector. We use the number of elements, n_s , in an information set to measure the amount of information an OFDI project has. Therefore, if $n_s^i > n_s^j$, the investing firm has more information in market i than in j . Current information helps infer future information following Bayesian updating process. Thus, I_s and I_r ($r > s$) are positively correlated—more information at I_s improves the information in I_r in the future.

The current period return of a possible OFDI in k markets depends on the contemporaneous information set. This return can be positive (profit) or negative (loss) and assumed to be known for the decision period. Let us denote the return of project i at period s as $r_{i,s}$.

The risk-neutral firm shall choose market i (out from k markets) that, according to the firm's estimation, yields the maximum present value of returns in designated investment periods ($T-s$,

and $s = t, t+1, \dots, T$). We note this present value of expected returns from project i , $R_{i,s}$ and define it recursively⁴ as

$$R_{i,s} = r_{i,s} + \beta E_s(R_{i,s+1}), \quad (1)$$

where β is a discount factor. When the OFDI project ends, the scrap value $R_{i,T}$ is given exogenously. Therefore, the expected return from project i depends on the uncertain streams of future returns throughout the investment periods. To explicitly incorporate this uncertainty in the model, we rewrite equation (1) as

$$R_{i,s} = r_{i,s} + \beta p(I_{s+1}|I_s)R_{i,s+1}, \quad (2)$$

where the expected return at $s+1$, $E_s(R_{i,s+1})$, depends on the probability of realization of information set I_{s+1} . I_{s+1} in turn is inferred from I_s , the currently available information. $p(I_{s+1}|I_s)$ is a posterior probability Bayesian updated from the given information, I_s . As more knowledge and information are accumulated at period s , the prior I_s , improves (e.g. n_s increases) and the propensity of better estimation for $R_{i,s+1}$ increases.

In each period, the firm chooses one out of k projects that maximize the return in equation (1) to invest. In addition, the firm has an option choosing to forfeit all those projects but to defer the investment to the next period if the maximum return of those projects does not exceed a reservation rate V_t . As noted in Bernanke (1983), this reservation rate can be defined as the “expected value of deferring commitment,” which is strictly non-negative as the following:

$$V_s = \beta E_s\{\text{Max}(R_{1,s+1}, \dots, R_{k,s+1}, V_{s+1})\}$$

In essence, a firm chooses the FDI project i , if and only if both of following conditions exist:

$$R_{i,s} = \text{Max}(R_{1,s}, \dots, R_{k,s}) \quad (3)$$

and

$$R_{i,s} \geq V_s \quad (4)$$

In contrast to Bernanke (1983), who carefully studied equation (4) about the value of information gained by waiting until the next period, we focus on equation (3) where we analyze

⁴Irreversible investment should be deep forward-looking as opposed to using myopic decision rules (Arrow, 1968; Sargent, 1980).

how a firm may maximize the chance of choosing the optimal OFDI project by investing it as a sequential OFDI. Presumably, sequential OFDI possesses more information than non-sequential OFDI projects because it accumulated experiential information that is not available for non-sequential ones. Indeed, any firm could equally draw from the “global pool” of public knowledge about a market. However, some insider knowledge is only available through previous OFDI experience in the same or similar market, thereby creating asymmetric or disproportional firm-specific knowledge advantage over other markets.

Now, let us assume that equation (4) holds at period s . The firm decides to invest a project in market i , the expected return of which tops all other markets. However, due to the stochastic environment of future periods, the ex post information set, I_{s+1} , in period $s+1$ may be significantly different from ex ante one in period s ; that is, due to uncertainty, $p(I_{s+1}|I_s)$ is low enough that results in significant error in estimating future returns and the expected returns of project i is not the highest one among k projects in period $s+1$ anymore. Let us use $X_{i,s+1}$ to notate this error,

$$X_{i,s+1} = R_{i,s+1} - \text{Max}(R_{1,s+1}, \dots, R_{i-1,s+1}, R_{i+1,s+1}, \dots, R_{k,s+1}) \quad (5)$$

$X_{i,s+1}$, a negative value, is the difference between the NPV of returns from project i and the best returned project in period $s+1$.

Had it no significant liquidation cost, the firm would liquidize project i and switch to the best project, say project j , in period $s+1$. However, the irreversible property of OFDI prevents the firm to do so. Since the firm has run project i for one year at period s and realized return $r_{i,s}$, as demonstrated in Figure 1, as long as the error, $X_{i,s+1}$, is less than $r_{i,s}$, the running project i remains optimal. Because project j was forfeited and had no return in period s .

Thus, to maintain the committed project optimal consistently throughout the investment periods, the firm needs to meet the following condition:

$$r_{i,s} \geq -\beta E_s(X_{i,s+1} | X_{i,s+1} \leq 0, I_s) \quad (6)$$

Equation (6) shows that the realization of project i as the optimal depends on the forecast error of project i relative to other projects. More specifically, if and only if the discounted forecast error is less than the current period return, $r_{i,s}$, should the choice of project i remain

optimal. In this sense, $r_{i,s}$ is the worst possible projection error that is allowed to occur in period $s+1$ in order to guarantee project i being the optimal choice.

We then borrow the framework of *VaR* in finance literature to demonstrate the purpose of our model—how sequential OFDI, relative to non-sequential OFDI, helps maximize the probability of the chosen project i to be optimal. Within the *VaR* framework and assuming that $X_{i,s+1}$ is normally distributed $\sim N(\mu_{X_{i,s+1}}, \sigma_{X_{i,s+1}})$, the *VaR* of $X_{i,s+1}$ can be expressed as:

$$VaR = \mu_{X_{i,s+1}} - z \times \sigma_{X_{i,s+1}}, \quad (7)$$

where *VaR* is the worst possible forecast error, z is the z -score of confidence level for a normal distribution, $\mu_{X_{i,s+1}}$ is the mean, and $\sigma_{X_{i,s+1}}$ is the standard deviation of forecast error. According to equation (6), the chosen project i will not remain optimal unless $VaR_{X_{i,s+1}}$ exceeds $-\frac{r_{i,s}}{\beta}$, the probability of which (as shown below) is conditional on information set I_s .

$$prob \left[\mu_{X_{i,s+1}} - z \times \sigma_{X_{i,s+1}} \geq -\frac{r_{i,s}}{\beta} \mid I_s \right] \quad (8)$$

Thus, the objective of OFDI firm to assure that project i remains optimal is to solve the maximization problem of equation (8) as the following:

$$\max_{I_s} \left\{ prob \left[\mu_{X_{i,s+1}} - z \times \sigma_{X_{i,s+1}} \geq -\frac{r_{i,s}}{\beta} \mid I_s \right] \right\} \quad (9)$$

For illustrative purpose, let us assume that the firm attempts to choose between a sequential OFDI that has information set I_s^i containing n_s^i elements and a non-sequential OFDI with information set I_s^j comprising n_s^j elements, where $n_s^i > n_s^j$. The sequential OFDI has better information than the non-sequential candidate as it contains more information elements. Using Bayesian updating, the mean and the variance of true estimation error x , which is observed as X with an error ε , can be expressed as (see Appendix A for the calculation):

$$\mu_{X_{i,s+1}} = E[x \mid X] = \frac{\tau_x \mu_x + \tau_\varepsilon X}{\tau_x + \tau_\varepsilon}$$

and

$$\sigma_{X_{i,s+1}}^2 = Var[x \mid X] = \frac{1}{\tau_x + \tau_\varepsilon},$$

where $\tau_x = \frac{1}{\sigma_x^2}$ and $\tau_\varepsilon = \frac{1}{\sigma_\varepsilon^2}$ represent the precision of forecasting estimation error, that, in turn, depends on the information available for forecasting. The more information is available, the higher is τ_ε . That is, $\tau_\varepsilon = f(I_s)$ and $f'(I_s) > 0$, where $f(\cdot)$ is a function. Apparently, τ_ε of sequential OFDI is greater than that of non-sequential OFDI as $n_s^i > n_s^j$.

Applying two equations above to equation (9), it is clear that a firm would choose a sequential OFDI to maximize equation (9). That is, investing a sequential OFDI in uncertain environment makes a firm more likely to be optimal than non-sequential OFDI, other things equal.

Our model implies that the information set I_s is critical to improve chances of a firm to choose an optimal project. Indeed, one critical constraint that hinders firms from international expansion is the lack of knowledge. In this environment of inadequate knowledge, firms have to make decisions based on consciously incomplete information sets (Johanson and Vahlne, 1977; 2009). Under our theory proposition, more knowledge and information that update the ex ante information set, I_{s+1} , reduces uncertainty and enhances the precision of return forecasting, thereby yielding accurate and reliable decision on the choice of optimal project.

Accumulating knowledge of a foreign market helps firms better manage and reduce uncertainty when operating in a foreign market, thus should increase the probability of an investment project being made in that market (Buckley and Casson, 1998). Sequential OFDI is one of common styles to accumulate asymmetrically more knowledge and information to reduce uncertainty (Chang and Rosenzweg, 2001; Johanson and Vahlne, 1977; 2009). The prior OFDI experience collects, in addition to publicly available information, experiential or insider knowledge and information that are not available otherwise. This informational advantage of sequential OFDI over other types of OFDI that presumably only have public information available would enable sequential OFDI to deliver a better return projection, resulting in maximum chance that the committed OFDI remains optimal in long term, *ceteris paribus*.

3. Some facts about China's OFDI and preliminary data analyses

We now turn to data and empirical analyses by first looking at some stylized facts about China's OFDI. China has conducted some OFDI activities since opening the "door" in the early 1980s. But the scale is fairly limited to early stages—mainly state-owned or local government-

owned enterprises were allowed OFDI with most locations based in Hong Kong. Up until 1997, China's total OFDI stock only stood around US\$ 2.4 billion (Cheung and Qian, 2009).

To sustain the economic reform process and promote global industry champions, Chinese government has issued series of policy directives since 1999, better known as “going global” or “step out” strategy, promoting Chinese overseas investment via direct investment. Consequently, Chinese OFDI started to take off in an astonishing pattern. As shown in Figure 2, the OFDI flow increased from US\$0.9 billion in 2000 to about US\$116 billion in 2014. Over a little more than a decade, China has accumulated about US\$729 billion of OFDI stock in 2014, which is 25 times as high as in the year 2000. China gradually has established itself as one of the important FDI capital providers—its global OFDI share has grown from almost 0 to about 8.5 percent in 2014 (Figure 1). Although the development path is impressive, most Chinese OFDIs are still in their infancy undergoing learning by experience.

During the period from 2000 to 2014, there were about 17,770 Chinese firms, including state-owned companies, FIEs, and private firms, from a wide spectrum of industrial sectors, involved in OFDI and completed 24,090 investment projects overseas. Some firms performed one-shot OFDI and stopped further investment due to various reasons, for example, failure on initial investment, while others undertook multiple OFDI projects to either explore different markets or implement a series of subsequent investments in the same market. Among all Chinese OFDI firms, one-shot OFDI firms account for 84.16 percent (14956 firms) and the rest 15.84 percent (2814 firms) firms carried out multiple OFDI activities during 2000–2014.

Chinese OFDI firms cope with uncertainty in foreign markets mainly rely on two strategies. First, to group few locations that hosted many Chinese peer OFDI firms, with whom they can share knowledge and information and learn from each other. From 2000 to 2014, 24,090 OFDI projects spread over 187 countries and regions. Majority of those projects are concentrated in a few destinations, such as Hong Kong, USA, Russia, Japan, and Australia. In fact, top 10 destinations received more than 60% of total Chinese OFDI (see Table 1). The tendency for agglomeration is even strong for one-shot OFDI—as shown in Column 3 of Table 1, 69.3% one-shot OFDIs are located in top 10 destinations.

The second strategy is to implement sequential OFDI to accumulate knowledge and information themselves. Sequential and agglomeration behaviors both help reduce perceived

uncertainty. However, sequential OFDI that learns from own experience to fend off foreign market uncertainty is less likely to agglomerate. Indeed, there are only about 46% of multiple-OFDI firms located in top 10 destinations. Further, as shown in the last column of Table 1, more subsequent OFDIs after firm's initial FDI experience in top 10 destinations chose to locate in countries other than the top 10 locations. Only 41.5% of subsequent OFDIs remain in the top 10 list of host countries.

Multiple-OFDI Chinese firms tend to make sequential OFDI. Temporarily defining the sequential OFDI as subsequent OFDI in the same market, we perform a non-parametrical data analyses about the probability of sequential OFDI. Imaging that firm i has investment experience in country j at time s , then the probability of sequential OFDI at time t is noted as $\Pr(l_{it} = j | l_{is} = j, t_0 \leq s < t)$ and the probability of subsequent OFDI to country j if it has no prior experience in j is expressed as $\Pr(l_{it} = j | l_{is} \neq j, t_0 \leq s < t)$. We calculate both probabilities for top 10 Chinese OFDI destinations and list them in Table 2. An average of 21% of Chinese OFDIs in top 10 destinations undertook sequential OFDI, while only about 2.6% chance that the subsequent OFDI is placed in a country where it has no previous OFDI experience. Vietnam is a salient example; almost one-third of Chinese subsequent OFDIs that go to Vietnam are sequential OFDIs. Only a fraction of 1% are willing to relocate to Vietnam.

4. Empirical evidence on the probability of sequential OFDI

In this section, we investigate the determinants of probability that a firm chooses sequential OFDI. In particular, we study how uncertainty factors implicated by our theory model affect the probability of a firm choosing sequential OFDI as opposed to either non-sequential OFDI or “forfeit and wait.”

4.1. The data and the extended definition of sequential OFDIs

Since we study firms' decision on whether to place OFDI overseas, firm-level OFDI data would be ideal. We extract data of 2422 Chinese firms that made FDIs overseas during 2000 to 2010. The selected firm sample is the result of name-matching in two databases, namely, “Directory of Chinese foreign investing enterprises” that listed the names of enterprises that made OFDI and “Chinese industrial enterprises database” that provides detailed accounting

information of Chinese industrial enterprises that have annual sales of over 5 million yuan (about US\$0.84 million⁵). In broad category, our firm samples comprise 251 SOEs, 793 FIEs, and 1376 PVEs. These firms are registered at 38 different industrial sectors, including textile, electronics manufacture, and energy (oil and gas) industry, etc.

Data are arranged to match the empirical strategy to test the implication of theoretical model. Specifically, when a firm plans for OFDI, it first assesses the opportunity and risk of potential locations and decides whether to invest in the current year or forfeit to the coming years. Once decided to commit immediately, it chooses the location of OFDI that pays the highest return based on its assessment. To accommodate this decision process, we organize our data in three-dimensional pooled data structure: firm \times year \times country. The time span is from 2000 to 2010, and we have 128 countries as the potential OFDI location.⁶ Note that our data set has a caveat that it only provides the year when a firm invests in a certain country without revealing the volume of OFDI. For instance, the data might show that in 2005, firm A invested in the US, but it did not provide how much the OFDI was. However, this information is sufficient for us to carry out our empirical analysis.

Literature papers usually define sequential OFDI as subsequent OFDI to the same country where a firm has the experience of prior OFDI (Chang and Rosenzweig, 2001; Davidson, 1980; Kugut, 1983; Kugut and Chang, 1996; Johanson and Vahlne, 1977). We consider this definition a narrow one as one may argue, for example, that a prior OFDI experience in Malaysia would have a similar effect on firm's decision to invest in Indonesia, which presumably has similar market as Malaysia. Thus, we attempt to extend the definition for "sequential OFDI" based on the concept of "similar markets" categorized below.

The knowledge accumulated through prior OFDI experience tends to reduce the risk of subsequent OFDI. Such risk reduction effect is the main driver for firms to make sequential OFDI. Arguably, the OFDI experiential knowledge accumulated in a country should be nearly equally applicable to countries in a similar income level or the same culture block, in terms of reducing the risk of subsequent OFDI. We define a similar market according to the "distance"

⁵The criteria have been raised to 20 million yuan since 2011.

⁶Each of these 128 countries hosts at least one OFDI project from our sample firm. There are perhaps other countries apart from these 128 countries that have Chinese OFDI, but it might be made by other firms outside of our firm sample or time spans (2000–2010). Consequently, we do not consider those countries in our empirical study.

between the host and home countries. This “distance” could be the measure from various perspectives. In addition to the commonly referred geographic distance, it also includes income level distance and culture distance that are found to have a profound implication on FDI (Hofstede, 1980; Souza and Peretiakko, 2005; Kolstad and Wiig, 2010; Bhaumik and Co, 2011). Similar strategy is used by Morales et al. (2014) who account for the “extended gravity” depending on whether the potential exporting destination sharing the continent, language, and GDP per capita with the previous exporting destination.

Thus, we define three types of similar markets based on whether the country is in the same income level categorized (notated as SM1) by World Bank (low-income, lower-middle, upper-middle, and high-income countries), the same World Bank income category plus sharing continent (SM2), and the same culture block that is defined in Ronen and Shenkar (1985) (SM3) (see Appendix B for details of different similar markets).

Now we define whether an OFDI project is sequential OFDI according to three newly defined types of similar markets. In principle, if a firm had previous presence of its OFDI in a country, all those subsequent OFDIs are defined as sequential OFDIs in that country. For the same reason, we define extended sequential OFDI as subsequent OFDI placed in a similar market country if the firm had prior OFDI in a country that belongs to the similar markets category. For example, the USA and UK are in the same category of high-income country. If firm A had OFDI establishment in the USA in 2002, an OFDI project placed in the UK by the firm A in 2005 is considered as an extended sequential OFDI of firm A. Following this strategy, we create data series, namely ExSeq1, ExSeq2, and ExSeq3, for the extended sequential OFDI based on the criteria of same income level (SM1), same income level and same continent (SM2), and same culture block (SM3), respectively. According to the definition of sequential and extended sequential OFDI, we count that, out of 3176 OFDI made by those Chinese firms during 2000–2010, there are 109 sequential OFDIs, and 341, 230, and 124 are Exseq1, Exseq2, and Exseq3, respectively.

4.2. Empirical specification and estimation

As the theory model suggests, one chooses to either forfeit-and-wait, sequential, or non-sequential OFDI, whichever maximizes the expected NPV of future returns. The probability of choosing the optimal project increases with the reliability of the return forecast that, in turn,

depends on the amount of information that reduces uncertainty. Thus, we expected that good foreign market, firm's ability to yield returns, and uncertainty or risk factors have positive impacts on the probability of sequential OFDI. To establish robustness of our studies, we examine a number of different regression specifications.

4.2.1. A conditional choice of sequential OFDIs

4.2.1.1 Empirical specification and explanatory variables

First, we use the theory of probabilistic choice of McFadden (1974) which allows analyzing the probability of dichotomous choice (sequential OFDI or not) and test the significance of independent variables leading to a sequential OFDI choice. A firm makes decision on an OFDI project is a random return maximization process as the following⁷:

$$R_{n,i} = V_{n,i} + \varepsilon_{n,i} = \alpha_i + s_n' \beta_n + x_{n,i}' \gamma_{n,i} + \varepsilon_{n,i}, \quad (10)$$

where n notates an individual firm⁸ and i represents the choice of the location (OFDI host country, $k = 1, 2, \dots, i, j, \dots$) of an OFDI. V is deterministic factors and ε is stochastic and reflects idiosyncratic factors of firm n and the choice location i . s_n represents characteristics of the investing firms that are constant across location choices, and $x_{n,i}$ represents factors that vary across location choices (host country's characteristics).

If $R_{n,i} > R_{n,j}$, $y_n = i$, the firm prefers choice i to j .

$$\begin{aligned} \text{Thus, } P_{n,i} &= \text{Prob}(y_n = i | i, j) = \text{Prob}(\varepsilon_{n,i} - \varepsilon_{n,j} < V_{n,i} - V_{n,j}) \\ &= \int I(\xi_n < V_{n,i} - V_{n,j}) f(\xi_n) d\xi_n, \end{aligned} \quad (11)$$

where $f(\xi_n)$ is iid Gumbel distribution. Under the assumption of independence of irrelevant alternatives (IIA) (Luce, 1959), the econometric specification of selection probability that can be estimated with logit method is expressed as follows:

$$\text{Prob}(y_n = i | s_n, x_{n,i}) = \frac{\exp(s_n' \beta_n + x_{n,i}' \gamma_{n,i})}{\sum_k \exp(s_n' \beta_n + x_{n,i}' \gamma_{n,i})} \quad (12)$$

⁷The discrete choice model usually drives from random utility maximization (RUM) to reach the choice probability (see McFadden, 1981, 1982, 1984). We drive it from random return maximization instead; the logic, however, is identical to RUM.

⁸Since we have a pooled cross-section and cross-time data set, each individual is represented by a firm-year pair, for example, Firm A at 2005.

Thus, determinants expected to affect the probability of a firm choosing sequential OFDI include both firm characteristics and home and host country factors. Indeed, FDI is a more comprehensive process than a simple return seeking on exploiting foreign market; it should include the adjustment to the changes within a firm and the firm's environment (Chang and Rosenzweig, 2001; Figueira-de-Lemos, et al, 2011; Song, 2002).

According to our theory proposition, factors that impact firm's ability to generate return, conditions of host country, and uncertainty factors that influence the precision of return projection under stochastic situation affect the probability for a firm to choose *i*. Thus, we include firm characteristics that reflect its capacity to generate current and future returns, as well as uncertainty factors of both host and source countries.

We use firm's total assets (*firm size*) and firm's industrial production share (*share*) to proxy firm's capacity to generate current and future returns of its committed OFDI project. Further, the risk attitude (or the degree of risk-averse) (Driver and Moreton, 1991) might affect firm's willingness to make efforts to accumulate information before implementing an investment project. Assuming that high leveraged firms are less risk-averse, we use the firm's *leverage* structure (the ratio of total liability to total asset) to represent firm's risk attitude. Conceivably, firm's international trade experience helps gain knowledge and reduces uncertainty (Conconi, Sapir, and Zanardi, 2016). We then add the *export share* (the share of exports in a firm's total sales) to the regression.

Regarding host country factors, we include GDP and GDP growth rate to proxy the host-country market size and market potential. Three uncertainty variables, *inflation* that reflects a country's overall macroeconomic risk, *exchange volatility* gauging the uncertainty of currency value, and *investment risk* from ICRG that particularly measures host country's political risk environment for FDI, are also included. In addition, high cost of exports to the host country would encourage Chinese firms to establish OFDI, thereby overcome the export cost barriers. Accordingly, we include the *cost of import* of host countries in the regression. While the cost of import motivates OFDI, the cost of doing business in a host country may discourage Chinese firms to set up OFDI project there. Thus, the *cost of business* is also included, and we expect the opposite effect of *cost of import* and *cost of business* to the probability of an OFDI.

In addition to factors pertaining to host countries, the involvement of home country (China) governments is essential. Wang *et al.* (2012) find that Chinese government involvement influences the level of overseas investment, its location (developed vs. developing countries) and its type (resource vs. market-seeking). Lu *et al.* (2014) find that government support reduces the need to accumulate experiential knowledge and capabilities from prior entry experience in a particular country when implementing sequential investment projects. They argue that government support alleviates market uncertainty for OFDI decision-making. We add the *government support* variable, and an interaction term of *government support* and *investment risk* to the regression to control the interaction between Chinese government support and host-country investment risk. The measurement of government support follows Lu *et al.* (2014) who measured the government support as a dummy variable, where 1 is assigned if both host country and the invested industry are in the preferential list of the Chinese government. Otherwise, 0 is assigned. We provide all variable definitions and data sources in Appendix C.

4.2.1.2 Estimation results

Now we interpret and discuss the empirical results on various factors that affect the probability of choosing sequential OFDI. We utilize the generalized mixed-effect logit regression technology that allows both fixed effect for each independent variable and random effect accounting for possible variations across individual firm and year. Maximum likelihood (ML) estimation yields the regression results.

We first estimate the specification with the commonly used sequential OFDI measurement (subsequent OFDI in the same country) as the dependent variable and the firm characteristics, macroeconomic, and country risk factors as explanatory variables. The estimation results are reported in Column (1) of Table 3. Since we use ML, the results can be interpreted as the elasticity of sequential OFDI with respect to the changes in those factors.

Two of the firm's characteristics—*Size* and *Share*—associated with the firm's return-generating ability are significant. Both large firm size and high domestic production share increase the probability of sequential OFDI. In fact, a 1% increase in the firm's domestic industrial production share is found to be associated with a magnitude of 3.8% increase in the chance that the firm seeks overseas market with sequential OFDI. With the gradually saturated Chinese domestic market, increasing shares in domestic market is difficult and costly in

comparison to seeking new demand in foreign markets. Thus, an OFDI that designated to facilitate export activities in a foreign market may turn out to be a better choice than further exploiting domestic market, resulting in higher chances of OFDI. The other two risk-related firm characteristics—*Leverage* and *Export share*—are not significantly estimated. It seems that the firm's risk attitude and trade experience have no impact on the firm's choice on sequential OFDI.

The host country market size (*GDP*) and market potentials (*GDP growth*) attract Chinese sequential OFDI. These findings are in line with the export facilitating purpose of Chinese OFDI. One percent increase in *GDP* and *GDP growth* raise the chance of sequential OFDI by 0.46% and 0.13%, respectively. Both *Cost of business* (the cost of business start-up in host countries) and *Cost to import* are estimated to be against our expectation, both insignificant though.

The main goal of this study is to analyze uncertainty factors. Our theory implies that increased uncertainty in foreign market leads firms to take sequential OFDI that bears less risk, thanks to the added knowledge it accumulated in a host country relative to non-sequential OFDI. Indeed, macroeconomic uncertainty, measured by *Inflation*, is estimated to have positive impact on the presence of sequential OFDI, suggesting that firms are concerned about macroeconomic uncertainty. In order to rein in macroeconomic risk, Chinese firms are more likely to take sequential OFDI. *Investment risk* is estimated significantly and is in line with our model implication. The result shows that a 1% increase in the risk level in host countries leads Chinese firms to invest 0.26% more sequential OFDI relative to non-sequential OFDI and “wait and forfeit.” This effect is almost four times stronger than that of macroeconomic uncertainty. We do not find significant impact from exchange rate volatility on choice of sequential OFDI.

Government support alleviates uncertainty that OFDI firms have to deal with, resulting in firms' less reliance on sequential OFDI. Therefore, we expect to find government support reduces the probability of sequential OFDI. However, our estimation suggests otherwise. This unconventional finding perhaps because, during our sample periods, Chinese government's “Going Global” supporting policy motivated all types of Chinese OFDI, sequential OFDI included (Wang et al, 2012). Despite this out-of-expectation results, further investigation on the interaction between *government support* and *investment risk* by examining the interaction term (*Government support*Investment risk*) reveals some intuitive results. Government support not only directly impact the occurrences of sequential OFDI, but also goes through the interaction

between *government support* and *investment risk* and indirectly impact to the probability of sequential OFDI. As the result shows, with Chinese government support, the effect of *investment risk* in the host country to sequential OFDI is reduced by 0.39%. Government support reduces the impact of *investment risk* by providing, for example, financial subsidy and knowledge and information collected through diplomatic channels and intensive research carried out by government agencies (Lu et al, 2014). Thus, when a firm assesses the effect of *investment risk* to decide what type of OFDI to commit (e.g. cautious investment type), the necessity of sequential OFDI appears to be lower under the umbrella of government support. It hence leads to less presences of sequential OFDI, *ceteris paribus*.

Now, let us turn to examine how those factors affect the extended sequential OFDI—the subsequent OFDI to countries in the similar market block? Doing so, we replicate the previous regression by replacing the dependent variable with three extended sequential OFDI measurements—Exseq1, Exseq2, and Exseq3, and Columns (2), (3), and (4) of Table 3 report the results, respectively. Except for a few changes in estimate significance, the main results are remarkably similar as the one in Column (1) indicating that prior OFDI experience indeed supports a firm to establish subsequent OFDI projects in other countries that are in the similar market block, and our estimate results are robust across different measurements for sequential OFDI. Those changes are listed in order. First, *Cost of business* becomes significant in column (2). It seems Chinese sequential OFDI is willing to bear high cost in order to stay in the similar income level markets. Second, *Cost to import* turns into significant—indicating high *cost to import* significantly reducing the probability of sequential OFDI, which is against our expectation that high *cost to import* motivates Chinese firms to overcome trade barriers and set up OFDI in an export destination. The reason perhaps is the fact that most current Chinese OFDIs are sales offices to facilitate Chinese exports as opposed to manufacturing facilities. This suggests that Chinese firms are looking to divert OFDI to other countries with lower *cost to import* rather than setting up more OFDIs to help exports. Thus, high *cost to import* deters Chinese sequential OFDI. Third, *Inflation* loses the significance in two regressions, so do *Share*; but the signs are correct.

In sum, factors associated with generating returns, for example, firm capacity and host-country market opportunities, increase firms' sequential OFDI presence. Increasing macroeconomic uncertainty or riskier investment environment motivates firms to take up

cautious types of OFDI projects—sequential OFDI. These findings are in line with our theory proposition.

4.2.2. A multinomial choice problem

An observation has been made in our theory that a firm decides either forfeit-and-wait or OFDI that could be sequential or non-sequential OFDI, whichever yields the highest expected return. In this section, we examine the probability of sequential OFDI from an alternative perspective to the previous section where a firm chooses sequential OFDI against otherwise, including non-sequential OFDI and forfeit-and-wait. We now assume that the firm first decides whether to commit or forfeit and wait; once decided to commit, it chooses either sequential or non-sequential OFDI whichever yields better returns.

Against this perspective, we resort to the multinomial logit specification that allows us to study the probability of sequential and non-sequential OFDI against forfeit-and-wait. The framework of McFadden (1974), laid out in the previous section, still applies, except that it is necessary to modify equation (12) into the following:

$$Prob(y_{n,i} = fw|s_n, x_i) = \frac{\exp(s_n' \beta_{fw} + x_i' \gamma_{fw})}{\sum_{l=fw,sq,nsq} \exp(s_n' \beta_l + x_i' \gamma_l)} \quad (13)$$

$$Prob(y_{n,i} = sq|s_n, x_i) = \frac{\exp(s_n' \beta_{sq} + x_i' \gamma_{sq})}{\sum_{l=fw,sq,nsq} \exp(s_n' \beta_l + x_i' \gamma_l)} \quad (14)$$

$$Prob(y_{n,i} = nsq|s_n, x_i) = \frac{\exp(s_n' \beta_{nsq} + x_i' \gamma_{nsq})}{\sum_{l=fw,sq,nsq} \exp(s_n' \beta_l + x_i' \gamma_l)} \quad (15)$$

where fw , sq , nsq , respectively, denote the choice of forfeit-and-wait, sequential, and non-sequential OFDIs and equation (13), (14), and (15), respectively, express how the probability of fw , sq , and nsq are calculated, provided that they are determined by a set of firm characteristic (s_n) and country factors set (x_i). In order for this system to be identified, we have to arbitrarily set one of choice (e.g. forfeit and wait) to be the reference option and set $\exp(s_n' \beta_{fw} + x_i' \gamma_{fw}) = 1$. Thus, the equation system described previously becomes

$$Prob(y_{n,i} = fw|s_n, x_i) = \frac{1}{1 + \sum_{l=sq,nsq} \exp(s_n' \beta_l + x_i' \gamma_l)} \quad (16)$$

$$Prob(y_{n,i} = sq|s_n, x_i) = \frac{\exp(s_n' \beta_{sq} + x_i' \gamma_{sq})}{1 + \sum_{l=sq,nsq} \exp(s_n' \beta_l + x_i' \gamma_l)} \quad (17)$$

$$Prob(y_{n,i} = nsq|s_n, x_i) = \frac{\exp(s_n' \beta_{nsq} + x_i' \gamma_{nsq})}{1 + \sum_{l=sq, nsq} \exp(s_n' \beta_l + x_i' \gamma_l)} \quad (18)$$

thereby, the relative probability of sequential OFDI and non-sequential OFDI relative to the forfeit-and-wait option is defined as:

$$\frac{Prob(y_n=sq|s_n, x_i)}{Prob(y_n=fw|s_n, x_i)} = \exp(s_n' \beta_{sq} + x_i' \gamma_{sq}) \quad (19)$$

$$\frac{Prob(y_n=nsq|s_n, x_i)}{Prob(y_n=fw|s_n, x_i)} = \exp(s_n' \beta_{nsq} + x_i' \gamma_{nsq}) \quad (20)$$

The parameter vector, β' and γ' , are estimated from maximum log likelihood function. One can interpret the estimated result as the marginal effect of an independent variable leading to the probability of choosing sequential or non-sequential OFDI over forfeit and wait. Similar to the conditional logit procedure in the previous section, we include both firm characteristics and the macroeconomic indicators, and uncertainty factors in the host country and from the home country in the regression.

We report the results of (19) in Column sq1, sq2, sq3, and sq4 and equation (20) in Column nsq1, nsq2, nsq3, and nsq4 of Table 4. As Table 4 shows, in general, factors affect the probability of sequential and non-sequential OFDI relative to forfeit and wait in a similar fashion as demonstrated in Table 3.

Further, comparing the estimated marginal effect on sequential and non-sequential OFDI, we spot a few differences. For example, *investment risk* positively affects both sequential and non-sequential OFDI at 99% confidence level. The differences are that 1% increase in *investment risk* is associated with about 0.18% more chance of non-sequential OFDI, whereas it has an average of 0.3% impact on the probability to choose sequential OFDI. This comparison exposes the fact that, relative to forfeit and wait, decisions pertaining to sequential OFDI or non-sequential OFDI perhaps depends on very careful assessment on some common factors, for example, investment risk level in host country. In principle, high level of uncertainty tends to lead firms to choose more of cautious sequential OFDI *vis a vis* non-sequential OFDI. Indeed, even in the host countries where OFDI receives preferential policy support from government, investment risk's impact in the choice of sequential OFDI substantially higher than non-sequential (−0.24 vs. −0.15 on an average). The support from government increases both

sequential and non-sequential OFDI relative to choice of “forfeit and wait.” Macroeconomic uncertainty influences non-sequential OFDI more than sequential.

Another noteworthy result is that *cost of business* is estimated to be positive and significant for non-sequential OFDI, while insignificant in sequential OFDI. A plausible explanation is that Chinese firms use non-sequential OFDI to compete in exporting markets where they are not previously established, and the cost of business start-up is high. Indeed, Chang and Rhee (2011) find that firms may adopt rapid international expansion that can enhance the firm’s performance when the global competition is fierce. Along with their finding and combining the estimated result of *cost to import* that high cost of import hinders non-sequential OFDI (1% increase in *Cost of import* is associated with 1.5% less non-sequential OFDI), we may interpret that Chinese non-sequential OFDI deviates from existing OFDI establishment to explore new markets where *cost of business* is competitively high but *cost to import* may be low.

4.2.3. Nested logit regression that deals with IIA.

Both conditional logit and multinomial logit assume that the probability of choice i is independent to other alternatives—a property called IIA. If the odd ratio of i is not truly independent to other alternatives, the estimated parameter may be inconsistent (Hausman and McFadden, 1984). In our study, we shall not rule out the dependence among alternatives, in particular, when firms choose alternative locations across similar markets. Thus, we use Nested Logit specification (Greene, 2002) where we group the alternatives into subgroups that allow the variance to differ across the groups while maintaining the IIA assumption within each group.

Consistent to the categorization of similar markets, we group all Chinese OFDI host countries into four subgroups according to World Bank classification, namely lower income, lower middle income, upper middle income, and high income. We allow countries within each group to be correlated while assuming that countries are independent across income level groups. Although firms may not necessarily make decisions sequentially, we consider firms go through a sequential decision process, in which they first choose the income level group, then decide which country in that chosen group to place the OFDI project. This procedure can be depicted in a tree structure (Figure 3).

The random return maximization problem of equation (10) is still true, but the probability of equation (12) is revised as:

$$Prob(y_n = i) = Prob(y_n = i|G_m) * Prob(G_m),$$

$$\text{where } m \text{ indexes four groups, } prob(y_n = i|G_m) = \frac{\exp(s_n' \beta_n + x_{n,i}' \gamma_{n,i} / \rho_m)}{\sum_{j \in G_m} \exp(s_n' \beta_n + x_{n,j}' \gamma_{n,j} / \rho_m)},$$

$$Prob(G_m) = \frac{\exp(x_{n,m}' \gamma_{n,m} + \rho_m IV_{n,m})}{\sum_m \exp(x_{n,m}' \gamma_{n,m} + \rho_m IV_{n,m})}, \text{ and the inclusive value, } IV_{n,m} = \ln \sum_{j \in G_m} \exp(s_n' \beta_n + x_{n,j}' \gamma_{n,j} / \rho_m), \text{ and } 1 - \rho_m \text{ is the correlation inside each group.}$$

Following Greene (2002), estimation is done using a limited information two-step maximum likelihood approach. First, we estimate locational parameters, $\gamma_{n,i}$, by treating the locational choice within groups as a conditional logit model and compute inclusive values $IV_{n,m}$ for all groups. Then, we estimate β_n with a conditional logit regression among groups with the inclusive value as an explanatory variable and the predicted $Prob(G_m)$.

Nested logit regression results are reported in Table 5. Hausman and McFadden's (1984) LR test's rejection of IIA assumption suggests us to pinning down the issue of correlation among alternatives to avoid inconsistent estimation results. Allowing alternative correlation, however, substantially lowers the significance of our estimation (the Coef. Column of Table 5). None of the firm's characteristics are significant in any subgroup. According to nested regression results, firm-level factors might not be important for a firm's sequential OFDI locational decision. Regarding country factors, none except for three uncertainty factors—investment risk, government support, and their interaction term—are significant at 10% level. This may highlight, in accordance to our theory proposition, the importance of uncertainty factors to the choice of sequential OFDI. These results are also in line with previous results: host-country investment risk level pushes up sequential OFDI, and Chinese government support reduces the impact of investment risk on sequential OFDI. Overall, Chinese government support encourages more sequential OFDI. However, one may notice that the number of observations⁹ in nested logit regression was substantially reduced to 7733, which is significantly different from the sample size in previous sections. Hence, we shall interpret the results in this section with caution.

⁹STATA 13 dropped 8725 cases (658,155 observations) due to no positive outcome or multiple positive outcomes per case.

4.2.4. Estimating on samples with different firm types

Over three decades, China has gradually opened its domestic market to foreign investors and implemented policies to attract FDI and reform the ownership structure by selective privatization which has dramatically shifted the corporate government structure. The dominance of the SOEs has been consistently eroded by the arrival of FIEs and thriving of PVEs. In addition to competing with SOEs for domestic market, most FIEs and PVEs are targeting overseas export markets. Indeed, SOEs' share of exports has gradually dropped from 75% of total Chinese export in 1994 to about 12% in 2013. On the other hand, PVEs' exports share has gradually grown from zero up to more than 20%. A similar situation seems to be occurring in the OFDI field. For instance, out of 15,300 Chinese OFDI enterprises in 2013, only 8% are SOEs that once accounted for more than 26% in 2006, while PVEs stand at 74.5% in 2013.

These different ownership structures imply different organization structures, incentive schemes, and operational and investment risk environment. In terms of OFDI, investment risk concern is not necessarily important for SOEs, as executing strategic orders from national leaders as opposed to maximizing return is perhaps the primary goal of SOEs OFDIs. Some high-risk OFDI stakes and their consequent failure lend support to our argument, for example, Citic Pacific's failed investment in West Australia iron ore mine.

PVEs, in general, have a strong profit incentive, and thus are quite sensitive to uncertainty factors. Relative to PVEs, the FIEs could have a wide array of instruments to manage the impact of investment risk, and thus, are less sensitive to risk. Different investment risk sensitivities are expected to place different weights on investment uncertainty when different types of firms make choice of sequential OFDI.

Thus, we separate the data into three subsamples according to the firm types, namely SOEs, FIEs, and PVEs, and repeat the mixed effect conditional logit regression in section 4.2.1 to test our postulation. The results are presented in Tables 6, 7, and 8, respectively. Indeed, there is a distinct difference between different firm types' choice on sequential OFDI in reacting to the changes in uncertainty. SOEs seem to concern about investment risk in host country only but are numb to government support, which is understandable as they are created and supported by the Chinese government financially and operationally.

By contrast, PVEs are very sensitive to all uncertainty factors—high inflation and investment risk in host countries make PVEs lean more toward sequential OFDI. They welcome the supportive policies from Chinese government—according to our estimate, government support could increase as much as 5% more possibility for a PVE to invest sequential OFDI.

FIEs turn out to be the most insensitive firm types to uncertainty in terms of their choice of sequential OFDI. Neither investment risk in host countries nor government support from China has an impact on their decision. The reason for this is probably because of their well-equipped risk hedge instrument and rich international experience in FDI (after all, their thriving in China may prove their ability to manage risk and uncertainty). They seem to concern the overall macroeconomic situation; however, it is so only in one out of four regressions in Table 7 and at 5% significance level.

In addition to uncertainty factors, factors concerning the generation of return have different impacts on sequential OFDI from three firm types. While the size of FIEs and PVEs positively affect their decision of sequential OFDI, it is the industry dominance (*Share*) that leads SOEs to invest more with sequential OFDIs. PVEs concern both the market size (*GDP*) and market potential (*GDP growth rate*) of host countries; FIEs worry more about market size than its market potential, while SOEs do the opposite. Many Chinese SOE OFDIs are on natural resource exploitation to serve China's desire to acquire natural resources rather than exploring or deepening export markets for their products as most PVEs and FIEs do. Therefore, it is conceivable that we find *cost to import* has no effect on SOEs' sequential OFDI. By contrast, high cost of import significantly reduces the chances of sequential OFDI from both PVE and FIE. This is particularly true for FIEs as they have plenty of FDI experience and a broad range of locations to choose from, which makes it easy for them to re-direct their OFDI to where the cost of import is lower.

Despite some salient differences in results from firm types, it highlights that risks and uncertainty are important factors in deciding firms' choice of sequential OFDI. High risk-sensitive firms are found to be more careful, therefore more likely to choose sequential OFDI, which is precisely in accordance to our theory model proposition. In sum, our results are proven to be robust and tested on different sample selections.

5. Concluding remark

We study the links between uncertainty, information, and sequential OFDIs with an illustrative theory model developed from Bernanke (1983) framework and by using various empirical models. In the theoretical model, we identify the plausible channel that uncertainty affects a firm's decision on its OFDI locational choice of either sequential OFDI or non-sequential OFDI.

Due to the irreversibility of OFDIs, an investing firm has to be in deeply forward looking and forecast the overall returns throughout the investment periods in order to choose the optimal OFDI project. Uncertainty is a major cause for an error occurrence in a future return projection, which, in turn, leads to choosing non-optimal or failed project. Intuitively, accumulating knowledge and information reduces uncertainty, thus improving precision of future return forecast, resulting in higher probability of choosing an optimal OFDI project.

From the *VaR* theory perspective, it is conceivable that, when facing increasing uncertainty, a firm tends to choose sequential as opposed to non-sequential OFDIs, in that sequential OFDIs heuristically accumulate, sometimes create, asymmetrically more knowledge and information that aid in forecasting future returns more accurately, thereby reducing both the mean and the standard deviation of the forecasted error.

To test the theory, we use Chinese firm-level OFDI data to examine what factors, especially uncertainty factors, affect firms' choice on sequential OFDI that possesses uncertainty reduction advantage. The decision-making processes on sequential OFDI are analyzed from two different perspectives. First, assuming that a firm decides to choose either sequential OFDI or others, including forfeit-and-wait and non-sequential OFDI, we apply McFadden (1974) conditional logit model that allows us to analyze the probability of dichotomous choice. Second, we assume that the firm first decides whether to forfeit or wait or commit. Once committed to invest, the firm then assesses both sequential and non-sequential OFDI to decide which type it is ready to invest on. A multinomial logit regression then is used to investigate what factors influence the odd ratio of sequential OFDI against the choice of forfeit and wait.

In summary, we find that uncertainty factors, including inflation (macroeconomics uncertainty) and investment risk in host countries, are positively associated with the

probability of sequential OFDIs. Chinese government support that supposedly reduces uncertainty is found to mitigate the impact of investment risk to the choice of sequential OFDIs. The Chinese government support overall increases the probability of both sequential and non-sequential OFDIs. This is in line with the astonishing increase of Chinese OFDIs since 2004 when the Chinese government implemented its “going global” policy. Host-country market size and market potential attract more Chinese sequential OFDIs, while cost of import diverts sequential OFDIs. Regarding individual firm characteristics, both firm size and firm’s domestic industrial output share matter, whereas firm’s debt leverage structure and exporting experience seem ineffective when considering firm’s decision on sequential OFDIs.

To gain the robustness of our findings, we resort to an alternative model specification—the nested logit regression that deals with the issue of IIA assumption, which could cause inconsistent estimation results (Hausman and McFadden, 1984). In addition, we regress on subsamples categorized according to different firm types, namely SOEs, FIEs, and PVEs, each of which may have different sensitivity to uncertainty. Evidently, both approaches allow us to confirm the robustness of our aforementioned findings. When studying on subsamples, we find that SOEs are more concerned about investment risk in host country but are numb to Chinese government support. By contrast, all uncertainty factors significantly influence PVEs’ decision of sequential OFDIs. Increasing uncertainty leads PVEs to be more cautious therefore are prone to choose sequential OFDIs. FIEs are managed by experienced FDI investors who have an array of hedge instruments that allow them to choose any type of OFDIs regardless of the level of uncertainty. Hence, uncertainty is not found to affect FIE’s sequential OFDI decision-making. Overall, our empirical findings are robust and in accordance to our theory proposition.

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Appendix A: Bayesian Information Updating

We consider a simple Bayesian normal updating case. Suppose that we are interested in the estimation error for future returns of an OFDI project, notated as x . x is observed with error:

$$X = x + \varepsilon,$$

where

$$x \sim N\left(\mu_x, \sigma_x^2 = \frac{1}{\tau_x}\right)$$

and

$$\varepsilon \sim N\left(0, \sigma_\varepsilon^2 = \frac{1}{\tau_\varepsilon}\right).$$

ε is independent of x , σ_x^2 refers to the variance of estimation error, and τ_ε represents the precision of projection for the estimation error.

$$\begin{aligned} \text{Var} \begin{bmatrix} X \\ x \end{bmatrix} &= \begin{bmatrix} E[(X - \mu_x)^2] & E[(X - \mu_x)(x - \mu_x)] \\ E[(x - \mu_x)(X - \mu_x)] & E[(x - \mu_x)^2] \end{bmatrix} \\ &= \begin{bmatrix} \sigma_x^2 + \sigma_\varepsilon^2 & \sigma_x^2 \\ \sigma_x^2 & \sigma_x^2 \end{bmatrix}. \end{aligned}$$

Then, the updated or posterior for x , given $X = x^*$ is normally distributed.

$$(x | X = x^*) \sim N(E[x | X = x^*], \text{Var}[x | X]),$$

where

$$\begin{aligned} E[x | X = x^*] &= \mu_x + \frac{\sigma_x^2}{\sigma_x^2 + \sigma_\varepsilon^2} (x^* - \mu_x) \\ &= \frac{\tau_x \mu_x + \tau_\varepsilon x^*}{\tau_x + \tau_\varepsilon} \end{aligned}$$

and

$$\text{Var}[x | X] = \sigma_x^2 - \frac{(\sigma_x^2)^2}{\sigma_x^2 + \sigma_\varepsilon^2}$$

$$\begin{aligned} &= \frac{\sigma_x^2 \sigma_\varepsilon^2}{\sigma_x^2 + \sigma_\varepsilon^2} \\ &= \frac{1}{\tau_x + \tau_\varepsilon}. \end{aligned}$$

Regarding both the conditional expectation and variance above, the last line expresses them in terms of precision. The projection precision of x , given as X is $\tau_{x|X} = \tau_x + \tau_\varepsilon$. When observed X is updated with accumulated knowledge and information, the projection precision of x improves.

Appendix B: Similar market category

1, World Bank income level:

Low income	AFG, BEN, BGD, ETH, GIN, KEN, KHM, MDG, MLI, MOZ, NER, NPL, PRK, SLE, TCD, TGO, TJK, TZA, UGA, ZAR, ZWE
Lower middle income	ARM, CIV, CMR, COG, EGY, GHA, GTM, IDN, IND, KGZ, LAO, LKA, LSO, MAR, MMR, MNG, NGA, PAK, PHL, SDN, SEN, SYR, UKR, UZB, VNM, WSM, YEM, ZMB
Upper middle income	AGO, ALB, ARG, AZE, BGR, BIH, BLR, BRA, BWA, COL, CUB, DZA, GAB, HUM, IRN, JAM, JOR, KAZ, LBY, MEX, MUS, MYS, NAM, PAN, PER, ROM, SRB, SYC, THA, TUR, VEN, ZAF
High income	ARE, AUS, BEL, BHR, BMU, BRN, CAN, CHE, CHL, CYM, CYP, CZE, DEU, DNK, ESP, EST, FIN, FRA, GBR, GNQ, GRC, HKG, HRV, IRL, ISR, ITA, JPN, KOR, KWT, LTU, LUX, LVA, MAC, NLD, NOR, NZL, POL, PRT, QAT, RUS, SAU, SGP, SVK, SWE, URY, USA

2, continent:

Asia Pacific	AFG, ARE, ARM, AUS, AZE, BGD, BHR, BRN, HKG, IDN, IND, IRN, ISR, JOR, JPN, KAZ, KGZ, KHM, KOR, KWT, LAO, LKA, MAC, MMR, MNG, MYS, NPL, NZL, PAK, PHL, PRK, QAT, RUS, SAU, SGP, SYR, THA, TJK, UZB, VNM, WSM, YEM
Africa	AGO, BEN, BWA, CIV, CMR, COG, DZA, EGY, ETH, GAB, GHA, GIN, GNQ, KEN, LBY, LSO, MAR, MDG, MLI, MOZ, MUS, NAM, NER, NGA, SDN, SEN, SLE, SRB, SYC, TCD, TGO, TZA, UGA, ZAF, ZAR, ZMB, ZWE
Europe	ALB, BEL, BGR, BIH, BLR, CHE, CYP, CZE, DEU, DNK, ESP, EST, FIN, FRA, GBR, GRC, HRV, HUN, IRL, ITA, LTU, LUX, LVA, NLD, NOR, POL, PRT, ROM, SVK, SWE, TUR, UKR
North America	BMU, CAN, CYM, USA
South America	ARG, BRA, CHL, COL, CUB, GTM, JAM, MEX, PAN, PER, URY, VEN

3, culture black Ronen and Shenkar (1985)

<i>Anglo</i>	GBR, USA, AUS, CAN, IRL, NZL, ZAF
<i>Germanic</i>	AUT, DEU, CHE
<i>Nordic</i>	DNK, FIN, NOR, SWE
<i>Latin European</i>	FRA, BEL, ITA, PRT, ESP
<i>Latin American</i>	ARG, VEN, CHL, MEX, PER, COL
<i>Near East</i>	TUR, IRN, GRC
<i>Far East</i>	MYS, SGP, HKG, PHL, IDN, THA, VNM
<i>Arabic</i>	BHR, ARE, KWT, SAU, OMN
<i>Independent</i>	JPN, BRA, IND, ISR

Appendix C: Variable definitions

SOFDI: Sequential OFDI is defined as the subsequent OFDI made by a Chinese firm to a foreign market where it has prior OFDI experience. We further broaden the definition of sequential OFDI as subsequent OFDI placed in similar markets, which are categorized according to three standards, namely World Bank income level, income level and share continent, and culture block (Ronen and Shenkar, 1985). Source: Directory of Chinese foreign investing enterprises.

Size: Firm size measured by firm's total assets in logarithm value. Source: Chinese industrial enterprises database, various year.

Share: Firm's output share in China's total industrial production. Source: Chinese industrial enterprises database, various year.

Leverage: Firm's debt leverage structure, measured by the ratio of total debts to total assets. Source: Chinese industrial enterprises database, various year.

Exports share: Firm's exports share in its total sales. Source: Chinese industrial enterprises database, various year.

GDP: OFDI host country's GDP in current US\$ and logarithm value. Source: World Bank Development Indicators (WDI).

GDP growth: OFDI host country's GDP growth rate in logarithm value. Source: World Bank Development Indicators (WDI).

Cost of business: Cost of starting a business in the host country in % of income per capita. OFDI host country's GDP in current US\$ and logarithm value. Source: World Bank Development Indicators (WDI), Doing Business.

Cost of imports: the cost of imports in the host country in US\$ per container. Source: World Bank Development Indicators (WDI), Doing Business.

Inflation: the annual percentage changes in consumer prices. Source: World Bank Development Indicators (WDI).

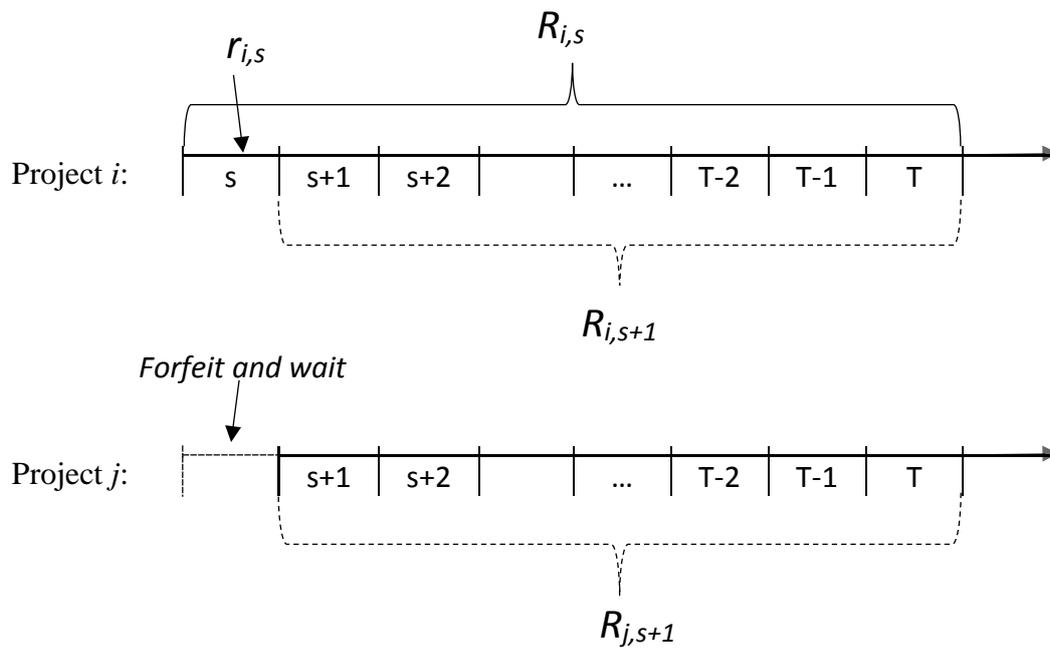
Exchange volatility: the standard deviation of renminbi to USD exchange rate, calculated from period average monthly data. Source: IMF IFS.

Investment risk: the investment profile index extracted from ICRG. Source: ICRG, International Country Risk Guide.

Government Support: an indicator variable that is given value of 1 if OFDI is invested in the preferred industry and located in a country that is encouraged by Chinese

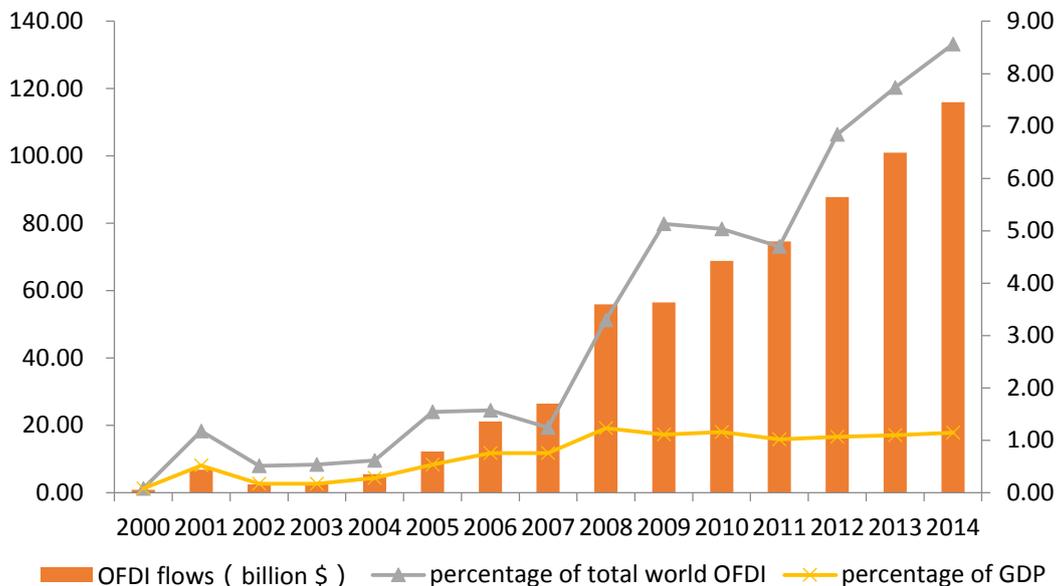
government to invest. Otherwise, 0 is assigned (Lu et al, 2014). Source: Guidance Catalogue of Countries and Industries for Overseas Investment, 2003, 2005, 2007, and 2009.

Figure 1:



Project i is the optimal project in period s . However, in period $s+1$, project j could turn to optimal if $R_{j,s+1} > R_{i,s+1}$. Project i remains optimal if and only if $r_{i,s} > X_{i,s+1} = R_{j,s+1} - R_{i,s+1}$.

Figure 2:



Data Sources: UNCTAD Dataset and "Directory of Chinese foreign investing enterprises"

Figure 3:

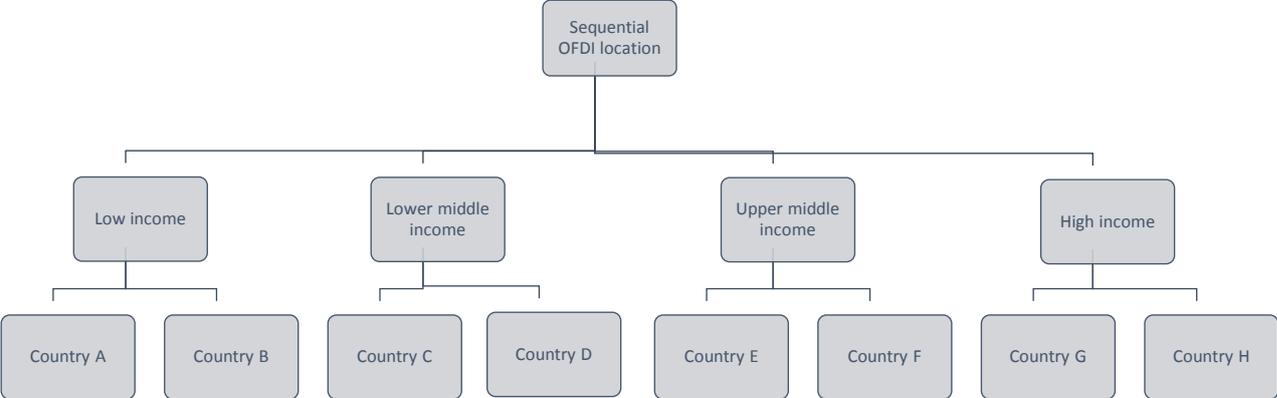


Table 1: Top 10 locations for different groups of Chinese OFDI firms 2000–2014

Ranking	Full sample	One-shot OFDI firms	Multiple OFDI firms		
			Full sample	First OFDI	Subsequent OFDI
1	HKG	HKG	HKG	HKG	HKG
2	USA	USA	USA	USA	USA
3	RUS	RUS	RUS	RUS	RUS
4	JPN	JPN	DEU	DEU	SGP
5	VNM	VNM	SGP	JPN	AUS
6	AUS	KOR	JPN	VNM	IDN
7	DEU	AUS	ARE	ARE	ARE
8	SGP	DEU	VNM	SGP	DEU
9	KOR	SGP	AUS	IDN	VNM
10	ARE	CAN	IDN	AUS	JPN
Percentage	60.3%	69.3%	46.5%	50.7%	41.5%

Sources: “Directory of Chinese foreign investing enterprises”

Table 2: Probability of choosing a top 10 location given different initial conditions

Country	$\Pr(l_{it} = j l_{is} = j, t_0 \leq s < t)$	$\Pr(l_{it} = j l_{is} \neq j, t_0 \leq s < t)$
HKG	23.49%	9.39%
USA	18.25%	4.96%
RUS	26.07%	1.41%
SGP	11.81%	2.03%
AUS	25.00%	1.68%
IDN	22.58%	1.46%
ARE	24.09%	1.28%
DEU	15.58%	1.43%
VNM	28.67%	0.99%
JPN	14.38%	1.34%

Sources: “Directory of Chinese foreign investing enterprises”

Table 3: The results of generalized mixed-effect regression for sequential OFDIs

	(1)	(2)	(3)	(4)
<i>Size</i>	0.305*** (0.09)	0.353*** (0.07)	0.350*** (0.08)	0.395*** (0.08)
<i>Share</i>	3.836** (1.95)	4.155* (2.23)	3.801 (2.70)	3.067 (2.08)
<i>Leverage</i>	-0.197 (0.52)	0.162 (0.19)	0.162 (0.22)	0.036 (0.40)
<i>Export share</i>	0.062 (0.42)	0.300 (0.20)	0.132 (0.29)	0.192 (0.25)
<i>GDP</i>	0.456*** (0.13)	0.345*** (0.07)	0.282*** (0.08)	0.532*** (0.13)
<i>GDP growth</i>	0.132*** (0.05)	0.083*** (0.02)	0.083*** (0.03)	0.058* (0.04)
<i>Cost of business</i>	0.250 (0.20)	0.202** (0.10)	0.066 (0.11)	0.080 (0.16)
<i>Cost to import</i>	-0.636 (0.41)	-0.545** (0.22)	-0.575** (0.26)	-1.201*** (0.36)
<i>Inflation</i>	0.070** (0.04)	0.019 (0.03)	0.041 (0.03)	0.101*** (0.04)
<i>Exchange volatility</i>	-0.025 (0.07)	-0.052 (0.04)	-0.010 (0.05)	-0.078 (0.06)
<i>Investment risk</i>	0.259* (0.15)	0.310*** (0.09)	0.371*** (0.11)	0.334** (0.14)
<i>Government support *</i>	-0.391* (0.23)	-0.575*** (0.14)	-0.567*** (0.16)	-0.475** (0.23)
<i>Investment risk</i>				
<i>Government support</i>	3.857* (2.17)	5.274*** (1.34)	5.426*** (1.52)	4.056* (2.21)
<i>Constant</i>	-24.585*** (4.57)	-22.195*** (2.49)	-21.083*** (3.03)	-24.445*** (3.88)
<i>Firm random effect variance</i>	2.832* (1.64)	8.828*** (1.00)	15.314*** (1.50)	8.042*** (1.43)
<i>Year random effect variance (year)</i>	2.411 (2.45)	11.137*** (1.27)	12.598*** (1.70)	0.000 (0.00)
<i>#Fixed</i>	14	14	14	14
<i>#Random</i>	3	3	3	3
<i>Obs.</i>	663327	663327	663327	663327

Note: This table reports the results of mixed-effect conditional logit regression. Robust errors are in parentheses underneath coefficient estimates. “***”, “**”, and “*” indicate 1%, 5%, and 10% level of significance, respectively.

Table 4: The results of multinomial regression

	sq1	sq2	sq3	sq4	nsq1	nsq2	nsq3	nsq4
<i>Size</i>	0.286*** (0.08)	0.335*** (0.06)	0.324*** (0.07)	0.355*** (0.07)	0.049*** (0.02)	0.025* (0.02)	0.035** (0.02)	0.046*** (0.02)
<i>Share</i>	4.456*** (1.25)	5.818*** (1.73)	5.751*** (2.12)	4.805*** (0.83)	2.335*** (0.54)	0.957 (0.73)	1.636*** (0.60)	1.928*** (0.58)
<i>Leverage</i>	-0.157 (0.52)	0.158 (0.19)	0.154 (0.23)	-0.007 (0.42)	0.051 (0.05)	0.035 (0.05)	0.040 (0.05)	0.049 (0.05)
<i>Export share</i>	0.008 (0.45)	0.313* (0.19)	0.153 (0.27)	0.196 (0.21)	0.004 (0.07)	-0.033 (0.07)	-0.013 (0.07)	-0.004 (0.07)
<i>GDP</i>	0.447*** (0.13)	0.332*** (0.07)	0.271*** (0.08)	0.536*** (0.13)	0.500*** (0.02)	0.519*** (0.03)	0.518*** (0.03)	0.496*** (0.02)
<i>GDP growth</i>	0.144*** (0.05)	0.092*** (0.02)	0.093*** (0.03)	0.070** (0.03)	0.074*** (0.01)	0.074*** (0.01)	0.075*** (0.01)	0.077*** (0.01)
<i>Cost of business</i>	0.225 (0.19)	0.197** (0.09)	0.064 (0.10)	0.071 (0.16)	0.238*** (0.04)	0.244*** (0.04)	0.256*** (0.04)	0.245*** (0.04)
<i>Cost to import</i>	-0.536 (0.40)	-0.479** (0.20)	-0.500** (0.24)	-1.149*** (0.36)	-1.444*** (0.07)	-1.525*** (0.07)	-1.494*** (0.07)	-1.429*** (0.07)
<i>Inflation</i>	0.161 (0.32)	-0.063 (0.15)	0.037 (0.19)	0.526* (0.31)	0.181*** (0.05)	0.201*** (0.06)	0.188*** (0.05)	0.167*** (0.05)
<i>Exchange volatility</i>	-0.020 (0.07)	-0.055 (0.04)	-0.016 (0.04)	-0.073 (0.06)	-0.011 (0.01)	-0.007 (0.01)	-0.012 (0.01)	-0.009 (0.01)
<i>Investment risk</i>	0.253* (0.15)	0.295*** (0.08)	0.344*** (0.10)	0.306** (0.14)	0.188*** (0.03)	0.176*** (0.03)	0.175*** (0.03)	0.184*** (0.03)
<i>Government support</i>	-0.441* (0.24)	-0.585*** (0.13)	-0.589*** (0.15)	-0.537** (0.23)	-0.341*** (0.05)	-0.318*** (0.05)	-0.324*** (0.05)	-0.337*** (0.05)
<i>* Investment risk</i>								
<i>Government support</i>	4.024* (2.25)	5.430*** (1.26)	5.679*** (1.47)	4.734** (2.25)	3.267*** (0.44)	3.049*** (0.46)	3.083*** (0.46)	3.235*** (0.44)
<i>Constant</i>	-24.250*** (4.72)	-21.878*** (2.39)	-20.686*** (2.92)	-24.560*** (3.92)	-12.641*** (0.76)	-12.253*** (0.79)	-12.532*** (0.77)	-12.538*** (0.76)
<i>#Fixed</i>					28	28	28	28
<i>#Random</i>					5	5	5	5
<i>Obs.</i>					665928	665928	665928	665928

Note: this table reports the results of mixed effect multinomial regression. Robust errors are in parentheses underneath coefficient estimates.

“***, **, *” indicate 1%, 5%, and 10% level of significance, respectively.

Table 5: The results of nested logit regression for sequential OFDI

	Coef.	S.E.
Country		
<i>GDP</i>	0.628	(0.43)
<i>GDP growth</i>	0.018	(0.04)
<i>Cost of business</i>	0.100	(0.08)
<i>Cost to import</i>	-1.920	(1.31)
<i>Inflation</i>	0.145	(0.11)
<i>Exchange rate</i>	-0.044	(0.66)
<i>Investment risk</i>	1.067*	(0.65)
<i>Government support * Investment risk</i>	-1.302*	(0.71)
<i>Government support</i>	14.024*	(7.56)
Low middle income		
<i>Size</i>	3.517	(2.48)
<i>Share</i>	-17.839	(11.05)
<i>Leverage</i>	2.162	(3.71)
<i>Export share</i>	-38.219	(34.54)
Upper middle income		
<i>Size</i>	3.364	(2.49)
<i>Share</i>	-16.730	(11.15)
<i>Leverage</i>	1.493	(3.78)
<i>Export share</i>	-70.718	(70.80)
High income		
<i>Size</i>	3.842	(2.50)
<i>Share</i>	-13.730	(10.84)
<i>Leverage</i>	4.267	(3.52)
<i>Export share</i>	-37.019	(32.96)
Inclusive value parameters		
<i>Low income</i>	14.41151*	(8.55)
<i>Low middle income</i>	4.588473*	(2.69)
<i>Upper middle income</i>	4.092092**	(1.95)
<i>High income</i>	0.83509	(0.55)
LR Test for IIA	Ch2(4)= 32.48	
Obs.	7733	

Note: this table reports the results nested logit regression. Low income branch is the reference group. Robust errors are in parentheses underneath coefficient estimates. “****, **, *” indicate 1%, 5%, and 10% level of significance, respectively.

Table 6: The results of generalized mixed effect regression for SOE sequential OFDI

	(1)	(2)	(3)	(4)
<i>Size</i>	-0.042 (0.24)	-0.014 (0.15)	0.125 (0.22)	0.003 (0.21)
<i>Share</i>	8.196*** (2.02)	6.810*** (1.36)	7.110*** (1.72)	7.103*** (1.60)
<i>Leverage</i>	0.068 (1.25)	0.823** (0.35)	0.810 (0.52)	0.165 (1.21)
<i>Export share</i>	0.120 (1.23)	0.300 (0.62)	0.140 (1.18)	-0.083 (1.24)
<i>GDP</i>	0.486 (0.30)	0.432* (0.24)	0.404 (0.29)	0.535 (0.43)
<i>GDP growth</i>	0.277** (0.14)	0.167** (0.08)	0.252** (0.12)	0.064 (0.10)
<i>Costs of business</i>	0.882 (0.55)	1.012** (0.46)	0.935* (0.55)	0.541 (0.54)
<i>Costs to import</i>	1.195 (1.05)	0.254 (0.79)	0.897 (1.00)	-0.240 (1.15)
<i>Inflation</i>	0.030 (0.13)	0.098 (0.09)	0.034 (0.13)	0.197 (0.25)
<i>Exchange volatility</i>	-0.228 (0.18)	-0.309** (0.14)	-0.238 (0.18)	-0.412** (0.19)
<i>Investment risk</i>	0.726* (0.43)	0.970** (0.41)	0.836* (0.45)	2.248 (1.39)
<i>Government support *</i>	-0.591 (69.42)	-0.783 (66.11)	-0.694 (69.53)	-1.887 (56.26)
<i>Investment risk</i>				
<i>Government support</i>	-4.269 (655.82)	-2.991 (626.94)	-3.227 (658.25)	10.754 (512.69)
<i>Constant</i>	-40.941*** (12.30)	-36.113*** (8.37)	-40.537*** (11.53)	-50.585*** (17.55)
<i>Firm random effect variance</i>	0.000 (0.00)	0.000 (0.00)	0.000 (0.00)	0.000 (0.00)
<i>Year random effect variance (year)</i>	1.552 (1.89)	0.604 (1.03)	1.327 (1.70)	0.331 (0.99)
<i>#Fixed</i>	14	14	14	14
<i>#Random</i>	3	3	3	3
<i>Obs.</i>	59967	59967	59967	59967

Note: this table reports the results of mixed effect conditional logit regression. Robust errors are in parentheses underneath coefficient estimates. “***, **, *” indicate 1%, 5%, and 10% level of significance, respectively.

Table 7: The results of generalized mixed effect regression for FIE sequential OFDI

	(1)	(2)	(3)	(4)
<i>Size</i>	0.436** (0.18)	0.550*** (0.18)	0.505*** (0.20)	0.598*** (0.19)
<i>Share</i>	-0.511 (9.00)	-18.902 (20.29)	-12.643 (18.87)	-8.552 (14.18)
<i>Leverage</i>	0.212 (0.18)	0.471** (0.24)	0.517* (0.27)	0.287 (0.18)
<i>Export share</i>	0.192 (0.27)	-0.160 (0.59)	-0.112 (0.66)	0.163 (0.32)
<i>GDP</i>	0.568** (0.29)	0.458*** (0.12)	0.302*** (0.11)	0.509** (0.20)
<i>GDP growth</i>	0.053 (0.07)	0.043 (0.04)	0.025 (0.04)	0.032 (0.06)
<i>Costs of business</i>	0.153 (0.37)	0.183 (0.16)	0.069 (0.15)	0.045 (0.26)
<i>Costs to import</i>	-1.791** (0.78)	-0.947** (0.37)	-0.545 (0.37)	-1.175** (0.59)
<i>Inflation</i>	0.133** (0.06)	0.047 (0.04)	0.050 (0.03)	0.077 (0.06)
<i>Exchange volatility</i>	-0.126 (0.14)	-0.061 (0.07)	-0.024 (0.07)	-0.047 (0.11)
<i>Investment risk</i>	0.201 (0.26)	0.186 (0.14)	0.211 (0.14)	0.189 (0.22)
<i>Government support *</i>	-0.093 (0.55)	0.034 (0.28)	-0.026 (0.23)	-0.179 (0.56)
<i>Investment risk</i>				
<i>Government support</i>	0.267 (5.59)	-0.981 (2.87)	0.101 (2.23)	0.513 (5.64)
<i>Constant</i>	-21.104** (8.26)	-23.156*** (4.46)	-21.625*** (4.73)	-24.294*** (6.60)
<i>Firm random effect variance</i>	0.000 (0.00)	11.640*** (2.31)	16.851*** (3.12)	11.393*** (2.56)
<i>Year random effect variance (year)</i>	0.000 (0.00)	25.145*** (3.02)	34.401*** (4.00)	0.000 (0.00)
<i>#Fixed</i>	14	14	14	14
<i>#Random</i>	3	3	3	3
<i>Obs.</i>	191722	191722	191722	191722

Note: this table reports the results of mixed effect conditional logit regression. Robust errors are in parentheses underneath coefficient estimates. “***, **, *” indicate 1%, 5%, and 10% level of significance, respectively.

Table 8: The results of generalized mixed effect regression for PVE sequential OFDI

	(1)	(2)	(3)	(4)
<i>Size</i>	0.363*** (0.13)	0.409*** (0.08)	0.379*** (0.09)	0.434*** (0.11)
<i>Share</i>	-1.035 (5.73)	4.931** (1.98)	4.587** (2.22)	3.158 (2.46)
<i>Leverage</i>	-1.071 (0.81)	-0.592 (0.47)	-0.501 (0.54)	-0.673 (0.75)
<i>Export share</i>	-0.312 (0.78)	0.783* (0.42)	0.370 (0.50)	0.034 (0.71)
<i>GDP</i>	0.454*** (0.18)	0.263*** (0.09)	0.153 (0.11)	0.475*** (0.18)
<i>GDP growth</i>	0.162** (0.07)	0.075** (0.03)	0.078** (0.03)	0.079 (0.05)
<i>Costs of business</i>	0.159 (0.25)	0.111 (0.11)	-0.003 (0.13)	-0.006 (0.21)
<i>Costs to import</i>	-0.571 (0.54)	-0.535** (0.26)	-0.630** (0.32)	-1.511*** (0.50)
<i>Inflation</i>	0.056 (0.05)	0.015 (0.03)	0.040 (0.03)	0.107** (0.05)
<i>Exchange volatility</i>	0.069 (0.09)	-0.016 (0.05)	0.026 (0.06)	-0.013 (0.08)
<i>Investment risk</i>	0.208 (0.20)	0.290*** (0.11)	0.385*** (0.14)	0.305 (0.19)
<i>Government support * Investment risk</i>	-0.403 (0.29)	-0.630*** (0.15)	-0.656*** (0.19)	-0.499* (0.28)
<i>Government support</i>	3.882 (2.62)	5.919*** (1.45)	6.370*** (1.73)	4.550* (2.64)
<i>Constant</i>	-24.247*** (6.38)	-20.052*** (3.10)	-17.376*** (3.85)	-20.519*** (5.50)
<i>Firm random effect variance</i>	6.513*** (2.40)	4.054*** (0.95)	6.907*** (1.36)	4.691** (1.88)
<i>Year random effect variance (year)</i>	0.000 (0.00)	4.694*** (1.25)	3.092** (1.51)	0.690 (2.37)
<i>#Fixed</i>	14	14	14	14
<i>#Random</i>	3	3	3	3
<i>Obs.</i>	411638	411638	411638	411638

Note: this table reports the results of mixed effect conditional logit regression. Robust errors are in parentheses underneath coefficient estimates. “***, **, *” indicate 1%, 5%, and 10% level of significance, respectively.