Foreign Source of Technology on the Dynamics of Technological Capabilities: A Latent Transition Analysis for Firms in Developing Countries*

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Abstract

This paper proposes an econometric model with latent transition analysis (LTA) to investigate the dynamic patterns of firms' technological capabilities in Eastern European and Central Asian economies and examine the foreign source of technology on their transition over time. This study identifies three sequential stages along the development of technological capabilities for a large group of firms. Firms tend to stay in their existing stage, therefore their transition to higher level of technological capabilities needs extra effort. Different channels of foreign source of technology show diverse impacts on the transition probability of firms' technology capabilities. The direct source of foreign technology (FDI and technology license) is more important for firms with basic technological capabilities, while imported intermediate input plays a more significant role in improving firms' technological capabilities at the advanced level.

Keywords: technological capabilities, latent transition analysis, Markov process

JEL Classification: O33, O12, O52

1 Introduction

This paper aims at identifying the dynamic patterns of firms' technological capabilities in Eastern European and Central Asian economies and examining the impact of foreign source of technology on their transitions. The concept of "technological capabilities" has been widely used to analyze the successful catching-up of latecomer firms in East Asia, such as Korea and Taiwan, in 1980s and 1990s (Kim, 1997; Ernst and Kim, 2002; Hobday, 1995) and the failure of their counterparts in Latin American or India (Lall, 1987) since its original occurrence in World Bank project "the acquisition of technological capability". In their understanding the development of latecomer firms, those studies state certain sequential stages of technological capabilities along their reverse engineering process in virtue of analyzing either one firm or one industry in certain countries.

From the empirical point of view, firms in Eastern European and Central Asian economies are often absent from this area of analysis. Undergoing the transition to free economic regime and interacting with firms in other European Union economies, those firms are interesting objects for studying how the foreign advanced technology affect the development of latecomer firm's technology capabilities.

This paper contributes to the empirical literature by proposing an econometric model to identify the dynamics of technological capabilities for a large group of firms and generalizing the arguments from case study methodology about the determinants of their transition. It then sheds light on how latecomer firms in developing countries take advantage of foreign source of technology.

The results can be summarized as follows. (1) The estimated latent transition model endogenously identifies three sequential development stages for sampling firms, which basically confirms the arguments from previous case studies about the dynamic patterns of firms' technological capabilities. (2) A comparison of technological capabilities across Eastern European and Central Asian economies based on the posterior classification of firms shows that Slovenia and Croatia have relatively higher distribution of firms in advanced level of technological capabilities, meanwhile firms in Azerbaijan and Uzbekistan perform worst. (3) The transition analysis on firms' technological capabilities implies a hysteresis phenomena on a firm's developing its technological capabilities. They tend to stay in their existing stage, therefore extra effort is required for improving their technological capabilities. (4) Different channels of foreign technology show diverse impacts along the transition period based on this preliminary analysis. The direct source of foreign technology (FDI and technology license) is more important for firms with basic technological capabilities, while imported intermediate input plays more significant roles in keeping firms' technological capabilities at the advanced level.

The remainder of the paper is structured as follows. The next section summarizes the previous related studies. Section three presents the econometric models and their specifications. Section four describes the data source and measurements. Section five provides empirical results and their interpretations. The last section concludes the paper and discusses the future studies.

2 Literature Review

Despite of its comprehensive implicit and different focus among diverse studies, "technological capabilities" basically refers to a firm's ability to master the technology, explore it and create new technological knowledge. Kim (1997)'s definition, "the ability to make effective use of technological knowledge in efforts to assimilate, use, adapt and change existing technologies" states that it involves not only the formalized R&D, but also the commercialization of the technology and the customization to the local market.

2.1 Dynamics of technological capabilities

Two streams of studies focus on the development of technological capabilities. One of them follows the evolutionary approach (Kim and Nelson, 2000; Bell and Pavitt, 1993), understanding the path of a firm's acquisition of technological capabilities as the learning process and exploring the driving force behind of this process.

Another stream of studies adopts the strategic management and resource-based point of view, which tries to understand how a firm maintains the technological capabilities as the competitive advantages through knowledge management (Teece et al., 1997; Winter, 2003). It acts as a bridge between firm resources and the changing business environment. The role of organizational capabilities in that process is emphasized in those studies.

While the former focuses more on the catching up process and acquiring the minimum essential ability, the latter emphasizes to renew it after accumulating certain degree of capabilities (Dutrenit, 2004). Both of them point out the development process is a moving target and firms are heterogeneous in building technological capabilities in the sense that firms have to develop their own strategy and keep putting effort along the evolution of technology and changing environment (Pérez, 2001). More specifically, three dimensions are acknowledged in analyzing the technological capabilities, i.e., production, investment, and innovation capabilities, referring to the ability to maintain and operate the production facilities, the ability to expand capacity and establish new production facilities and the ability to create new technology and commercialization respectively (Kim, 1997).

Although different terminologies are adopted among studies, this accumulating process of technological capabilities has normally been categorized as three dynamic stage from basic to advanced level based on their performance in the above three aspects given that the nature of learning process suggests a sequence from simple to complex. This paper adopts Lall (1992)'s documentation: a firm with experience-based level of capabilities mainly does simple and routine tasks; After they accumulate certain knowledge, firms develop search-based capabilities, undertaking adaptive and duplicative tasks; Being at the advanced level, research-based firms are capable of implementing the innovative and risky task.

The development of technological capabilities is, however, non-linear, path dependent and technology specific because the development of technology itself is cumulative and firms have limited ability of calculation. Firms will try to diversify their technology by searching in zones that enable them to build on the firms existing technology base. Their performance to absorb the foreign technology depends on the strategy and effort they develop as well as their linkage other actors, which is heterogeneous among firms. This corresponds to the high investment in purchasing the machinery, upgrading the production line or training the workers, etc. at the initial stage. This process is described as developing from capital accumulation to technological assimilation by Nelson and Pack (1999) in their explanation of the Asian miracle. When aggregating to the industry and country level, the important linkage of different agents and actors as well as the national policy (Kim, 1997; Lall, 1998; Bell and Pavitt, 1993), e.g., trade or technology policy, are which leads to the discussion of national innovation system (Freeman, 1974).

2.2 Technological capabilities and foreign source of technology

The successful catching-up of firms in East Asian economies points out foreign advanced technology as one of the most important source for the accumulation of firms' technological capabilities from experience-based to research-based level. Firms' transition to the higher level of capabilities is a "reverse engineering" process (Kim, 1997).

Direct source of foreign technology is argued more important at the early phase of accumulation. FDI (Foreign direct investment) and technology license are the most direct way to access foreign technology. Kim (1997) argues that technology license and turnkey are especially important at the initial accumulating process of Samsung and Hyundai's catching-up. By OEM and training their own workers, firms develop their own strategy to absorb and implement the foreign technology. Once firms assimilate it, the foreign technology is not so important as initial stage. Firms start to compete in the international market after they developed their own capabilities.

Recent studies on firm-level productivity argue that trade contributes to technological capabilities as an indirect way by allowing local reverse engineering and access to new machinery and equipment. Exporters are observed to generate higher level of productivity in Slovenia after foreign sales are initiated (?) and certain industries in Taiwan (Aw et al., 2001). This so-called learning by exporting effect plays a more important role in upgrading the technological capabilities after firms proceed to the advanced stages when they create their own technology and compete in the international market. The imported intermediate input, which may embody the advanced technology from their foreign origin, is observed to have the significantly positive impact on total factor productivity (TFP) of importing firms (Almeida and Fernandes, 2008; Acharya and Keller, 2009). Further, variations in capital-goods trade explain firms' differences in productivity better than does overall trade (Eaton and Kortum, 1999).

This theoretical framework with respect to the accumulation of a firm's technological capabilities, however, has normally been analyzed with case studies methodology. Few study examines it with econometric analysis and generalizes to a large number of firms, for example, to identify the different stages along the development. Suffered from comprehensive implicitness which the "capability" concept covers and the insufficient data, previous studies analyze the relationship of technological capability and economic performance mainly focusing on large firms, in one single industry or country (Fagerberg et al., 2009). The multi-dimensional factors have to be aggregated in the way to provide an omnibus structure of technological capabilities in order to implement the econometric analysis. The current empirical analysis on technological capabilities adopts either a single indicator, such as R&D investment and on-job training (Aw and Batra, 1998), number of patent (Motohashi, 2008) or a comprehensive index generated with arbitrary combination (e.g., average) of different determinants (Archibugi and Coco, 2004). The latter is also applied to evaluate the technological capabilities at country level by UNCAD. Neither of them is capable of capturing the connotation of technological capabilities nor identifying their transitions.

This paper proposes a latent transition model to estimate simultaneously whether a firm belongs to the same category of technological capabilities and the probability of firms transitioning among latent states along time without pre-determined cluster structure. It tries to generalize the arguments from case study methodology by analyzing a large number of firms, which distinguishes this paper from previous studies. The determinants of such kind of transition are estimated with multinomial logistic regression by including different channels of foreign source of technology, i.e., FDI, technology license, imported intermediate input and export status.

3 Econometric Model and Estimation Strategy

A latent transition analysis (hereafter LTA), otherwise known as "hidden Markov model" in the field of engineering, is applied to estimate a firm's class membership with respect to their technological capabilities and to identify the dynamic stage of its development[1]. This model extends "latent class model" to repeated measurements (Visser et al., 2009).

3.1 Assumption and notations

A finite state space of firms' technological capabilities $S = S_1, \dots, S_n$, is not directly observable to analyst, but attached with three manifest dimensions of production performance, investment capability and innovation outcome.

Whether firms fell into certain identifiable latent state in terms of their technological capabilities is based on the measurement model on the above observable k factors $\mathbf{O} = (O_1, \dots, O_k)$. Each state has a probability distribution over the possible observable items. The probability distribution of observation variables in state i is denoted by B_i for $i = 1, 2, \dots, n$. Local independence is assumed, i.e., the observed variables are independent conditional on the underlying state. This is a common assumption in latent variable models.

[1] It is called as "latent Markov model" in the field of sociology and psychology. The model has been applied to study the learning process, speech recognition and the change of human behavior.

The transition dynamics of firms' technological capabilities is assumed to follow a first-order Markov process with the unobserved states, formalized as equation 1.

$$p(S_t|S_1, S_2, \ldots, S_{t-1}) = p(S_t|S_{t-1}) \tag{1}$$

This is in line with the idea that the development of technological capabilities is path dependent as argued by studies with an evolutionary approach (Nelson and Winter, 1982).

The transition model A provides transition probabilities $a_{ij} = P[S_{t+1} = S_j|S_t = S_i]$ for $1 \leqslant i, j \leqslant n$. The transition process is ergodic, that is, there are no absorbing states. Each level of technological capabilities could be reached from any other levels. Because the development of technological capabilities for firms is a moving target, if a firm with higher level of technological capabilities stops putting effort in accumulating along the development of technology, it will probably fall behind and switch to lower levels of technological capabilities.

The transition probabilities are influenced by foreign source of technology $\mathbf{F_t} = (F_{t1}, F_{t2}, \ldots, F_{tm})$.

3.2 Econometric model

Based on the above assumptions and notations, LTA with three states could be illustrated in figure 1.

A LTA can be used to generate an observation sequence, given n, k, B and the initial state distribution π. The probability of a firm's certain realization pattern $\mathbf{O_i} = (o_{i1}, \ldots, o_{ik})$ at time t can be written as

$$P[O_T = o_i|\lambda] = \sum_{S=1}^{n} \pi_1 B_{S_1=i}(O_1) \prod_{t=1}^{T} a_{S_{t-1}=i,S_t=j} B_{S_t=j}(O_t) \tag{2}$$

where λ is the parameter vector containing the parameters to model π, A, and B. The sum runs over all possible sequences $S_1, \ldots, S_T$ of the latent or hidden state sequence, and the product runs from $t = 2$ to T.

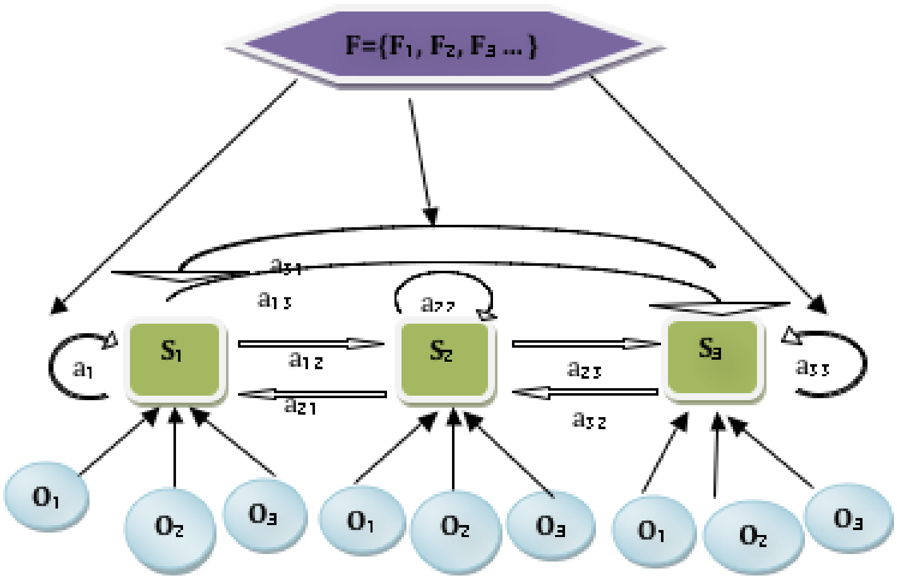


Figure 1: Latent Transition Model with 3 States

Under the assumption of local independence, the distribution function is $B_i(O_t) = \prod_{j=1...m} B_i(O^j)$. The probability that a firm has class membership S is achieved by maximizing the conditional probability in an iterative procedure.

$$s_t = \arg\max_{1 \leqslant i \leqslant n}\{\gamma_t(i)\} = \arg\max_{1 \leqslant i \leqslant n}\{p[s_t = S_i|\mathbf{O}, \lambda]\} \tag{3}$$

with $\sum_{i=1}^{n} \gamma_t(i) = 1$.

Heterogeneity could be controlled by specifying separate distribution functions for each measurement period. In this study, a latent transition logistic regression model proposed by Chung et al. (2007) is adopted to examine stage-sequential pattern firms' transition over periods to control the heterogeneity. A multinomial logistic regression for the transition probabilities is specified to model the probability of being in a current stage conditionally on the prior stage and covariates of foreign source of technology. Parameters of distributions are functions of time-varying variables $\mathbf{F_t}$, i.e.,

$a_{ij} = P(S_t = j|S_{t-1} = i, F_t)$. The transition probabilities from state i are modeled as a baseline category logit model:

$$log(a_{ij}/a_{i1}) = \alpha_j + \beta_{\mathbf{j}}\mathbf{F_t}, j = 2, \ldots, n \tag{4}$$

Parameters of LTA are estimated by optimizing the log-likelihood, with EM (expectation maximization) algorithm or gradients of the parameters for log-likelihood. The latter algorithm has advantages to deal with box constraints on parameters and general linear constraints between parameters (Visser and Speekenbrink, 2010). Akaike and Bayesian information criteria are used to judge the goodness of fit among models to determine the number of unobserved states, which performs well according to Paliouras (2007). Lower AICs and BICs normally suggest better fitting models.

Compared with its alternative – a two-step estimation of the conventional cluster and multinomial logistic regression, this LTA model is superior in the following three aspects. First, it is capable of estimating the state and its transition simultaneously by maximizing the possible state sequence. In this sense, it captures the individual's heterogeneity and dynamic mechanism to some degree. Second, there is no any pre-determined cluster structure or linear combination for the variables in the measurement model. Third, LTA is designed to deal with the discrete variable efficiently which more often occurs in the firm-level survey data in the field of economics.

4 Data

The data comes from Business Environment and Enterprise Performance Survey (BEEP), collected jointly by the European Bank for Reconstruction and Development, and the World Bank. The sample covers 23,570 firms with at least five full-time employees from 27 Eastern European and Central Asian economies between 2002 and 2009 with intervals of three to four years, providing detailed information about firm's characteristics, economic performance, innovation, investment environment, degree of competition, among others. Those sampling firms, designed to have a representative picture of industry for each economy, spread both manufacturing and service sectors in ISIC 4-digit industrial identification.

4.1 Measurement and specification

Seven variables categorized in three dimensions are included in the measurement model for estimating the stage of a firm's technological capabilities. Four variables are considered to identify four channels of foreign source of technology. Their measurements and respective specifications are explained in table 1.

4.2 Descriptive statistics

Observations with either missing value in variable SKL or in year 2007 are excluded from the following analysis due to the high sensitivity of the missing value setup in continuous variables to the estimation of this model and small proportion of surveyed firm in 2007.[2] It comes out 18,641 observations with three periods in 2002, 2005 and 2009.

Appendix 1 table shows the descriptive statistics of four continuous variables and categorical distributions of six discrete variables. Except the internationally recognized quality certificate (ISO) as a multinomial variable, all other categorical variables are binary. The correlation coefficients among seven variables in the measurement model and their corresponding significance level are reported in table 2. Although most of the correlation coefficients are highly significant except the correlation between job training and production capacity, only PDI and PCI shows a relatively higher level of correlation (0.46).

[2] Only 1,952 firms were surveyed in 2007, among which, 1,072 are from Bulgaria.

Table 1: Variables and Measurements

Factor	Dimension	Variable	Measurement	Type	Distribution*
O	Production capabilities	ISO	Internationally recognized quality certification	Categorical	Multinomial†
		SKL	Ratio of skilled workers to all employees	Continuous	Gaussian
		PRC	Production capacity	Continuous	Gaussian
	Investment decision	R&D	R&D investment	Categorical	Binary
		JBT	On-job training	Categorical	Binary
	Innovation outcome	PDI	The presence of new product in sales	Categorical	Binary
		PCI	Upgrading the production line in the past three years	Categorical	Binary
F	Direct	TCL	The usage of foreign technology license	Categorical	-
		FDI	The percentage of firms owned by private foreign organizations or individuals	Continuous	-
	Indirect	IMP	The propotion of all materials inputs or supplies purchased from foreign origins	Continuous	-
		EXP	Ratio of direct export to annual sales	Continuous	-

Note: *Refer to the distribution used in the measurement model.

† Except "yes" or "no", ISO includes in a category "in process" which is 1 if a firm applied for certification but not be granted yet.

Table 2: Correlation Table

	SKL	PRC	ISO	R&D	JBT	PDI	PCI
SKL	1						
PRC	0.02***	1					
ISO	0.03***	-0.02***	1				
R&D	0.04***	-0.07***	0.17***	1			
JBT	0.09***	0.01	0.19***	0.12***	1		
PDI	0.01*	-0.04***	0.2***	0.15***	0.16***	1	
PCI	0.07***	-0.02***	0.18***	0.16***	0.18***	0.46***	1

Note: Significance level * p<0.05, ** p<0.01,*** p<0.001

5 Results

The LTA is applied to the above data to differentiate experience-based, search-based and research-based levels of technological capabilities among firms as well as their transition over time.

5.1 Model selection and stage segment

In order to test the optimal number of stages along the development of firms' technological capabilities and identify the dynamic patterns, LTA models with 2-, 3- or 4-state are fitted to the data[3]. The continuous variable SKL and PRC are specified as a Gaussian distribution in the measurement model, with ISO, $R\&D$, JBT, PDI and PCI multinomial indicators in the model. Missing values in those multinomial variables are set as one category. Models are estimated with or without production capacity. Variables used to measure latent states are by nature unverifiable. This study selects the variables and the model in virtue of both goodness of fit measurement and the implicitness of the concept suggested by previous studies. Their corresponding goodness-

[3] "State" and "stage" are interchangable in the following description.

of-fit measurement is reported and compared in table 3 with a ‘pc’ denoting the inclusion of production capacity variable.

Table 3: Goodness-of-fit Measures for Model’s Selection

Models	logl	AIC	BIC	nfree	N
2	-67,062.7	134,183.3	134,410.3	29	18,513
3	-66,649.9	133,393.7	133,761.5	47	18,513
4	-66,639.6	133,413.2	133,937.5	67	18,513
2pc	-152,101.2	304,268.3	304,526.6	33	18,513
3pc	75,300.8†	-150,495.6	-150,080.8	53	18,513
4pc	76418.2†	-152,686.5	-152,099.5	75	18,513

Note: ‘-pc’ denotes a model with variable of production capacity.

† Positive log-likelihood occurs when the density function of continuous variable PRC is larger than 1.

The initial parameters of state distribution are set as (0.6, 0.4), (0.6, 0.3, 0.1), and (0.6, 0.3, 0.05, 0.05) for 2-, 3-, 4-state respectively.

As can be seen from table 3, three states specification has best goodness-of-fit statistics among LTA estimations with and without production capacity respectively. They have lower AICs and BICs (algebra value) compared to either 2- or 4-state models within each group, which indicates a three-stage pattern of technological capabilities among sampling firms. Including production capacity variable in LTA does not improve the goodness-of-fit measure. PRC is consequently excluded from the following analysis[4]. Three states LTA model without production capacity is preferred to analyze the transition probabilities. This result provides the tentative support for the 3-stage dynamic framework proposed by previous case studies. More details on

[4]It is dropped also because of the vague interpretation. It is not straightforward to argue the higher the production capacity is, the better technological capabilities is, or the other way around.

the characteristics of each state or stage along the development are reported in table 4.

Table 4: Stage Segment

	Production				Investment				Innovation			
	SKL*	ISO			R&D		JBT		PDI		PCI	
	Gaussian	No	IP†	Yes	No	Yes	No	Yes	No	Yes	No	Yes
S_1	0.47 (0.32)	0.93	0.00	0.06	0.40	0.07	0.76	0.24	0.90	0.10	0.83	0.17
S_2	0.51 (0.29)	0.89	0.00	0.11	0.44	0.15	0.66	0.34	0.35	0.65	0.07	0.93
S_3	0.54 (0.25)	0.48	0.02	0.50	0.26	0.50	0.23	0.77	0.25	0.75	0.12	0.88
N	18,513											
AIC	133,393.7											
BIC	133,761.5											

Note: *Standard deviation in the parenthesis. †'IP' is in process.

Probabilities at zero values of the covariates.

Parameters in each row of table 4 show the average performance of firms in each stage with respect to six variables in the measurement model based on 3-state LTA estimation. Firms on stage 3 show superior performance to the other two groups. They have the highest ratio of skilled workers (0.54) and are most likely to have an internationally recognized quality certifications (0.50), to invest R&D activities (0.50) and job training (0.77), and to undertake the product innovation (0.75) as well, with the middle level likelihood to do the process innovation (0.88), meanwhile firms in stage 1 display the worst performance. Therefore, it could be argued that the sequential stages along the development of a firm's technological capabilities is from S_1 with basic level, then S_2 and S_3 with relatively higher level. Accordingly, S_1, S_2 and S_3 are tagged as the experience-based, search-based and research-based stage of technological capabilities respectively. In search-based stage, firms show largest tendency to do the process innovation. It reflects the process of reverse engineering, i.e. firms invest in upgrading the production line before they engage in R&D activity and build their own technological capabilities.

The initial state probabilities have values $p_1 = 0.48$, $p_2 = 0.33$ and $p_3 = 0.19$. The estimated transition probabilities matrix is shown in table 5. The diagonal elements of this matrix have the largest value within each column or row, which could be interpreted as a certain level of hysteresis – firms in each stage have highest probability to remain in the same state in the next time period. The probability to stay in the previous stage, a_{11}, a_{22}, and a_{33} is 0.70, 0.61 and 0.89 respectively. As long as a firm develops the research-based level of technological capabilities, it tends to keep their advantages in the future. It is worth to note that firms in search-based level has a probability of 0.27 to lose their capabilities and fall down to experience-based level.

Table 5: Transition Probabilities Matrix

	Experience-based	Search-based	Research-based
Experience-based	0.70	0.22	0.09
Search-based	0.27	0.61	0.12
Research-based	0.10	0.00	0.89

Note: Probabilities at zero values of the covariates

5.2 Firms' technological capabilities across economies

According to the above LTA model and estimated parameters, every observation is allocated to their most probable stage membership of technological capabilities at each period based on the posterior estimation of the state sequence (Viterbi algorithm[5]). 8,186 observations load in stage 1 – experience-based level, with 7,177 and 3,150 in stage 2 and 3 respectively.

[5]See Rabiner (1989) for more technical details.

Table 6: Group of Firms' Technological Capabilities across Economies

	2002			2005			2009			Share of stages		
Economies	S_1	S_2	S_3	S_1	S_2	S_3	S_1	S_2	S_3	S_1	S_2	S_3
Albania	105	40	21	112	61	30	7	8	5	0.58	0.28	0.14
Armenia	107	45	18	163	158	30	24	54	34	0.46	0.41	0.13
Azerbaijan	121	33	12	264	69	16	46	56	18	0.68	0.25	0.07
Belarus	111	85	53	145	134	40	5	52	22	0.40	0.42	0.18
Bosnia	84	61	26	78	87	27	11	42	69	0.36	0.39	0.25
Bulgaria	131	82	34	192	79	28	30	32	29	0.55	0.30	0.14
Croatia	60	70	47	55	122	55	4	10	20	0.27	0.46	0.28
Czech Rep.	156	70	37	183	58	40	12	15	53	0.56	0.23	0.21
Estonia	81	50	36	103	80	33	15	33	39	0.42	0.35	0.23
Macedonia	117	40	6	118	56	26	23	56	35	0.54	0.32	0.14
Georgia	99	58	16	122	55	18	26	68	18	0.51	0.38	0.11
Hungary	167	32	39	377	138	93	25	53	23	0.60	0.24	0.16
Kazakhstan	155	59	33	354	190	41	47	84	39	0.55	0.33	0.11
Kyrgyz	88	57	24	95	78	29	29	49	14	0.46	0.40	0.14
Latvia	83	51	34	98	74	32	4	47	35	0.40	0.38	0.22
Lithuania	111	39	48	105	64	33	5	56	32	0.45	0.32	0.23
Moldova	88	62	23	159	160	27	32	51	27	0.44	0.43	0.12
Montenegro	9	8	0	10	7	0	12	13	8	0.46	0.42	0.12
Poland	252	139	101	519	309	145	39	44	57	0.50	0.31	0.19
Romania	114	98	40	307	219	72	69	51	58	0.48	0.36	0.17
Russia	285	144	70	334	208	53	63	299	216	0.41	0.39	0.20
Serbia	122	81	25	118	119	40	24	43	65	0.41	0.38	0.20
Slovakia	56	62	49	80	104	31	17	32	34	0.33	0.43	0.25
Slovenia	108	23	57	148	22	53	9	30	57	0.52	0.15	0.33
Tajikistan	94	57	23	109	71	20	19	79	14	0.46	0.43	0.12
Ukraine	179	153	69	242	292	57	95	271	96	0.35	0.49	0.15
Uzbekistan	165	62	32	252	42	6	70	42	9	0.72	0.21	0.07

Table 6 shows firms' stage distribution across economies along three survey periods. The share of overall observations in each stage across economies is reported in the last block column of table 6, illustrated in figure 2. It states that Slovenia has highest share (0.33) of firms in research-based level, followed by Croatia (0.28), Slovakia (0.25) and Bosnia (0.25), meanwhile most of the firms in Eastern European and Central Asian economies are still in the lower level of development. Large proportion of observations in Uzbekistan (0.72), Azerbaijan (0.68), Hungary (0.60) and Albania (0.58) loads in experience-based level. Among these economies, Ukraine (0.49), Croatia (0.46), Moldova (0.43) and Tajikistan (0.43) are observed the highest ratio of observations at search-based level. This result is only based on the sampling firm. To what degree this could be generalized to the whole economies depends on the sampling criteria[6].

5.3 Channels of foreign source of technology on transition probabilities

The impacts of foreign source of technology on transition probabilities are explored by including four variables – the usage of technology license (TCL), the proportion of imported intermediate input (IMP), the ratio of direct export to total sales (EXP) and the share of firms owned by foreign organization (FDI) – in a multinomial logistic model as specified in equation 4.

Observations with missing values in their variables IMP, EXP and FDI are dropped from the analysis in order to exclude the impact of missing value setup on the estimation. The generated subsample therefore covers 17,396 observations, with 93 firms surveyed in all three periods and 1,622 firms

[6]It will be too ambitious to argue this result reflects the performance of the whole economies. This part of analysis serves in illustrating the application of model by showing a snapshot of their performance.

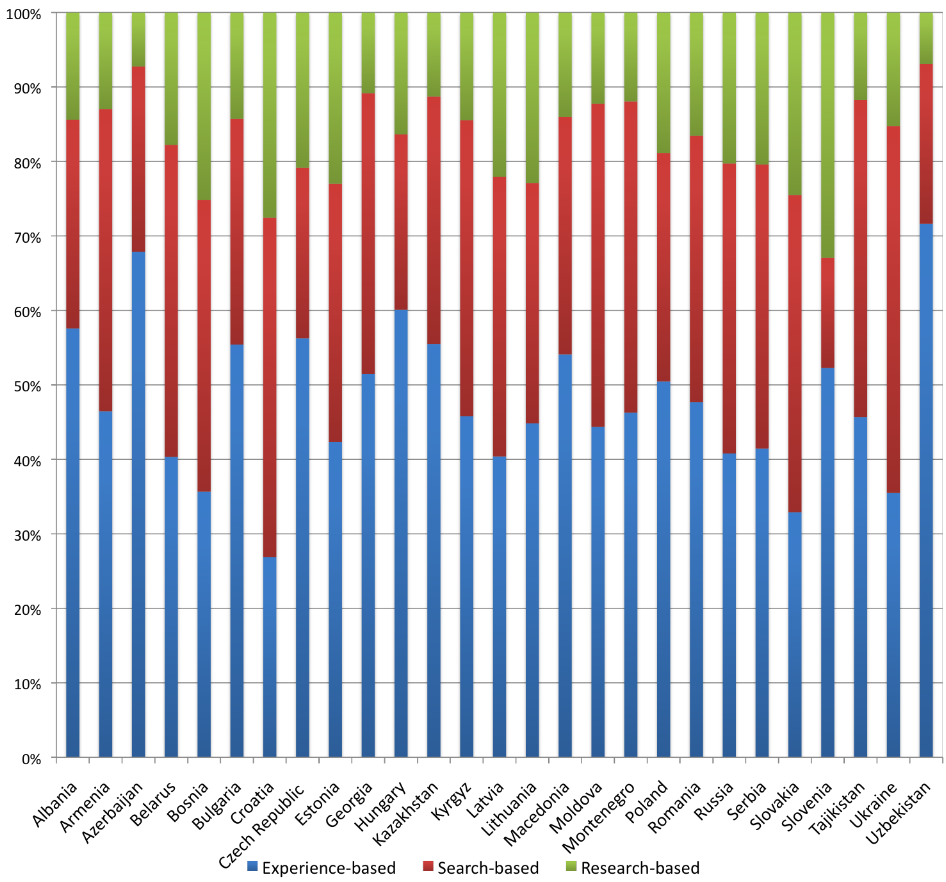


Figure 2: Stages of Firms' Technological Capabilities across Economies

two periods. The 3-state LTA with and without covariates on the transition probabilities are fitted to the above data. Table 7 compares the goodness-of-fit statistics for both models, with '-f' indicating the model including in the variables about foreign source of technology. The log likelihood ratio test (llr) shows that the inclusion of foreign source of technology improves the goodness-of-fit significantly, with log likelihood ratio 134.2 ($p = 0$). Model with covariates has lower AIC and BIC values as well. Therefore, it could be argued that foreign source of technology influences a firm' transition to different stages.

Table 8 reports the results of foreign source of technology on transition dynamics consequently. The default baseline category is stage 1 for each stage period, which leads to zero values in the first column of every stage block, with logodds scale for other columns.

The current result reveals quite diverse impacts among different channels of foreign source of technology on the transition probabilities as well as across different transition period. Technology license shows the largest impact on the transition probabilities, especially on the transition from stage 1 to stage 2 and 3. The usage of technology license will increase the log ratio of two probabilities $a12/a11$ and $a13/a11$ by 1.034 and 1.801 respectively. It also indicates large impact on the transition from stage 2 to stage 3 for firms in stage 2, with coefficient 1.329.

While FDI shows a certain effect on the transition probabilities from stage 1 to stage 2 and 3, it does not show important effects on stage 2 and 3. The measurement of FDI in this study is a rarely time-variant variable. It might be more proper to specify it as the covariate on the prior probability of firms' initial states.

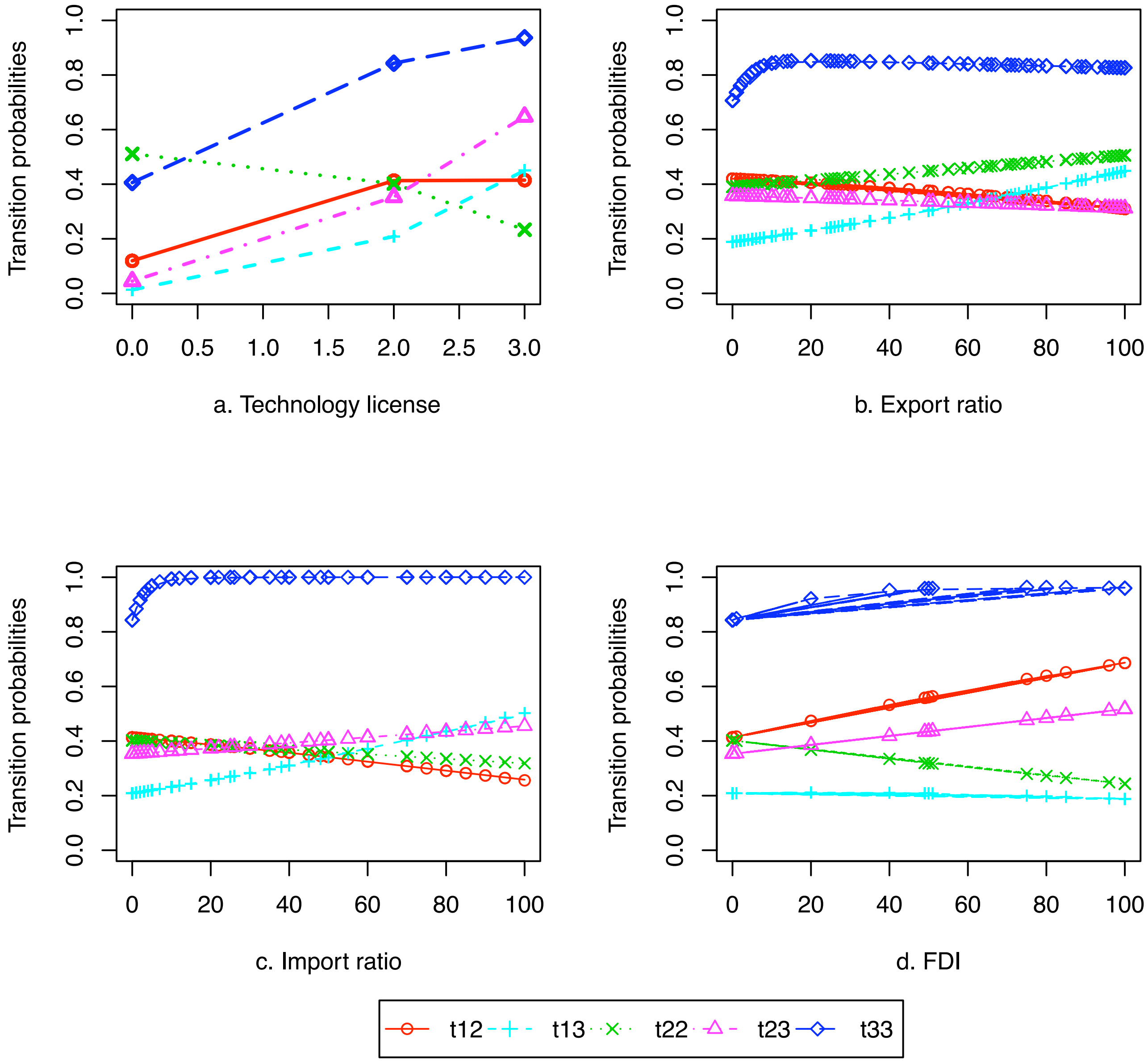
The imported intermediate input shows a relatively larger effect on firms' keeping their advanced technological capabilities rather than falling down to the experience-based level (0.258). So does export. Export shows the least impact on the transition probabilities with small coefficient values, although

Table 7: Goodness-of-fit Measures for Transition Probabilities with Covariates

Models	logl	AIC	BIC	nfree	llr	df(p)	N
3	-62,380.1	124,854.2	125,219.1	47			17,396
3f	-62,245.9	124,634.8	125,186.1	71	134.2	24(0)	17,396

Note: '-f' denotes a model with covariates of foreign source of technology.

The initial parameters of state distribution are set as (0.6, 0.3, 0.1) for both models.



Note: "txy" in the legend denotes the transition from stage x to stage y.

Figure 3: Foreign Technology Input on Transition Dynamics

Table 8: Transition Probabilities with Covariates

	S_1			S_2			S_3		
Var	S_1	S_2	S_3	S_1	S_2	S_3	S_1	S_2	S_3
TCL	0.000	1.034	1.801	0.000	0.178	1.329	0.000	-0.436	0.625
FDI	0.000	0.016	0.010	0.000	-0.005	0.004	0.000	-0.056	-0.007
IMP	0.000	0.002	0.013	0.000	0.006	0.002	0.000	0.260	0.258
EXP	0.000	-0.000	0.013	0.000	-0.002	0.003	0.000	-0.180	0.196
cons	0.000	-1.999	-4.332	0.000	0.082	-2.312	0.000	0.434	0.126
$p(trn)$	0.870	0.118	0.011	0.458	0.497	0.045	0.271	0.420	0.308
n	17,396								
AIC	124,634.8								
BIC	125,186.1								

Note: $p(trn)$ is transition probabilities. Probabilities at zero values of the covariates.

"cons" denotes the intercept item.

The t statistics and significance level have not been estimated yet.

its effect is more obvious on the transition or stay in the reseach-based stage (0.196).

In order to get comparable results, the marginal effects of each variable on the transition probabilities and their corresponding significance level are estimated and further illustrated in figure 3. A curve smoothing line between possible value of each channel of foreign source of technology and the predicted transition probabilities at the median point of other three variables is added. "txy" in the legend denotes the transition from stage x to stage y. This study is more interested in the transition dynamics from lower stage to higher stage or stay in the same higher stage, corresponding to five upper triangular elements in the transition matrix (excluding a_{11}). Therefore, five lines are plotted on each graph.

The usage of technology license improves the transition probabilities from stage 1 or 2 to stage 3 to largest degree for line t13 and t23 in figure 3a shows the steepest trend on the transition from point 2 (no technology license) to point 3 (the usage of technology license) at x-axis. It also has an positive effect on keeping the advanced level of the technological capabilities (line t33 in figure 3a). Export does not show much positive effect on the preferred transition of technological capabilities. It only shows the important effect on the transition from stage 1 to stage 3 (line t13 in figure 3b) and limited effects on staying stage 2 (line t22 in figure 3b). The imported intermediate input on the transition is more obvious for the transition from stage 1 to stage 3 (line t13 in figure 3c) and staying at stage 3 (line t33 in figure 3c). FDI plays a more important role on the transition from stage 1 to stage 2 (line t12 in figure 3d) and stage 2 to stage 3 (line t23 in figure 3d).

It could be argued that the direct source of foreign technology (FDI and technology license) is more important for firms with basic technological capabilities, while imported intermediate input plays more significant role in keeping firms' technological capabilities at the advanced level.

5.4 Robustness check

First, the correlated relationship and their significance level among variables used in the measurement model is estimated within each stage group of firms in order to check whether the assumption of local independence is fulfilled. As shown in table 9, there is no significantly high correlation among variables within each subgroup. Although some correlation coefficients are statistically significant, the highest level of correlation only occurs between $R\&D$ and ISO in stage 3 with the value of -0.24. This result could be considered as the support to the local independence assumption.

Second, the observations without missing values among continuous variables are extracted from the sample and pooled together. A two-step estimation of latent class model and cross-sectional multinomial logistic regression

Table 9: Correlation Coefficients in Each Stage

	SKL	PRC	ISO	R&D	JBT	PDI	PCI
				S_1, N=8,852			
SKL	1						
PRC	0.02**	1					
ISO	0.03***	-0.03***	1				
R&D	0.02	-0.05***	0.06***	1			
JBT	0.11***	0	0.08***	0.07***	1		
PDI	-0.01	-0.02**	0.01	-0.02**	0	1	
PCI	-0.03***	0.01	-0.09***	-0.2***	-0.15***	-0.14***	1
				S_2, N=6,487			
SKL	1						
PRC	0.03**	1					
ISO	-0.04***	-0.02	1				
R&D	0.02*	-0.08***	-0.04***	1			
JBT	0.04***	0.05***	-0.22***	-0.23***	1		
PDI	-0.1***	-0.02*	0	-0.13***	-0.11***	1	
PCI	0.01	0	0.01	-0.06***	-0.01	-0.05***	1
				S_3, n=3,174			
SKL	1						
PRC	0.02	1					
ISO	-0.01	0.05***	1				
R&D	-0.01	-0.06***	-0.17***	1			
JBT	-0.01	0.1***	-0.06***	-0.05***	1		
PDI	-0.03*	0.03*	0.14***	0.13***	0.1***	1	
PCI	0.03*	0.07***	0.15***	0.09***	0.14***	0.31***	1

Note: Significance level * p<0.1, ** p<0.05,*** p<0.01

is used to fit this pooled data. The 3-state latent class estimation generates 7,238, 6,780 and 3,378 observations at state 1, 2 and 3 respectively, similar with the result of 7,377, 6,954 and 3,065 from above LTA[7]. The cross-sectional estimation of multinomial logistic regression is reported in table 10.

Table 10: Cross-sectional Multinomial Regression on Transition

	S_1		S_2		S_3	
Var	S_2	S_3	S_2	S_3	S_2	S_3
TCL	0.678***	1.099***	0.164*	0.779***	0.129	0.573***
	(-7.13)	(-8.86)	(-6.9)	(-1.73)	(-3.59)	(-0.76)
FDI	0.009***	0.011***	-0.004	0.002	0.001	0.004
	(-2.67)	(-2.63)	(-0.49)	(-1.27)	-1.05	(-0.21)
IMP	0.001	0.009***	0.005*	0.006**	0.007*	0.007
	(-0.54)	(-3.05)	(-1.77)	(-2.52)	(-1.71)	(-1.63)
EXP	0.001	-0.000	0.007	0.003	0.001	-0.011**
	(-0.35)	(-0.00)	(-1.62)	-0.73	-0.31	(-2.02)
cons	-1.155***	-2.678***	-0.022	-1.417***	0.437*	-0.011
	(-9.11)	(-12.39)	(-7.15)	(-0.16)	(-0.04)	(-1.73)
N	746		686		376	
AIC	1,321.0		1,410.0		767.2	
BIC	1,367.2		1,455.4		806.5	

Note: z statistics in parentheses. Significance level * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Again, the default baseline category is state 1 for each state period. This estimation basically supports above LTA estimation, except a significantly negative effect of export on keeping the advanced level of capabilities in state 3 and magnitude of the coefficients on TCL and IMP in state 3. Technology license shows significantly positive coefficients on the transition

[7] The parameters of state segment are also similar. They are available on request

probability on stage 1, state 2 and keeping the advanced level on state 3, although the magnitude of the coefficients is decreasing along states and. FDI only shows significant positive sign for the transition to higher level in state 1.The imported intermediate input shows positive sign across all states. Export does not show significant impact on the transition of technological capabilities.

6 Conclusions

This paper proposes an econometric model with LTA to analyze the development of firms' technological capabilities and applies it to identify the dynamic pattern for firms in Eastern European countries and investigate the impact of different channels of foreign source of technology on the transition over time as well.

The evidence from firms in Eastern European and Central Asian economies fundamentally confirms the arguments from previous case studies about the dynamic patterns of firms' technological capabilities. The sampling firms are categorized as three stages along their development. A comparison of technological capabilities across Eastern European and Central Asian economies based on the posterior classification of firms shows that Slovenia and Croatia have relatively higher distributions of firms at the research-based (advanced) level of technological capabilities, while firms in Uzbekistan and Azerbaijan perform worst. The transition analysis on firms' technological capabilities implies that firms tend to stay in their current stage, therefore they need put extra effort in order to improve their technological capabilities.

Different channels of foreign source of technology show diverse impacts on the transition of firms' technological capabilities at different stages. The direct source of foreign technology (FDI and technology license) is more important for firms with basic technological capabilities, while imported intermediate input plays a more significant role in improving firms' technological capabilities at advanced level. The significant levels of the coefficients on transition probabilities haven't been estimated by far. More details are to be explored in the future.

These findings, however, are based on a relatively short time series dataset with small proportion of repeated observations. Since the enterprise survey is still undergoing, it is possible to get a longer and bigger dataset for this analysis in the near future. The country-specific factors, e.g. trade policy or investment environment could be included in explaining the transition probability of firms' technological capabilities in future studies.

Nevertheless, this paper provides a new analytical framework for studying a firm's technological capabilities and its transition over time.

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Appendix

Appendix 1. Descriptive statistics

Table 11: Descriptive Statistics

Continuous variables					Categorical variables						
Index	SKL	IMP	EXP	FDI		ISO	R&D	JBT	PDI	PCI	TCL
Min	0	0	0	0	Yes	3,073	3,391	7,020	7,655	10,462	876
Mean	0.5	31.4	10.4	10.4	No	15,260	7,088	11,473	10,816	7,996	11,598
Max	1	100	100	100	NA	96	8,034	20	42	55	6,039
SD	0.3	38.1	24.3	27.9	IP*	84					

Note: *IP means in process.