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Business Model Dynamics: A Longitudinal, Cross-sectional Case Survey

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Abstract

To maintain alignment with technology, regulation and market developments in the outside world, companies need to adapt their business models over time. As most literature has studied business models in a static approach, understanding is lacking on how external forces drive internal business model design choices. This paper studies which type of external drivers are most influential throughout the life cycle of business models. To do so, we surveyed 45 longitudinal case descriptions on business model dynamics of (networks of) organizations in various domains. Our results partly support our hypotheses. Market and technology drivers are most relevant in early stages of new business models, while regulation is far less important than we expected. These results mainly apply to small start-ups rather than large, established companies.

Keywords: business models, business model dynamics, case survey

1 Introduction

Business models are not static, but have to be revised over time to maintain fit with changing technology, market and regulatory conditions. Design choices once made during conceptualizations of initial service and underlying technology typically change during subsequent stages of market rollout and commercial exploitation. Insight in the links between external events and business model dynamics is highly relevant for practitioners to keep their business models adaptable and flexible over time. In addition, it would help refining business model design methodologies (e.g., Bouwman, et al., 2005a).

Much attention has been given to studying snapshots of business models at a certain moment in time, i.e. using a static approach. Although recent research has given some clues about business model dynamics (Andries, et al., 2006, MacInnes, 2005, Vaccaro and Cohn, 2004), the exact relation between external forces and business model design choices remains an unexplored area. This paper aims to study what type of external drivers are most important during the subsequent phases of business model life cycles. To do so, we conduct a case survey (Larsson, 1993, Yin and Heald, 1975) on a large set of existing case descriptions. The present analysis is a final step in the validation and refinement of a previously developed dynamic business model framework (Bouwman and MacInnes, 2006, Bouwman, et al., 2006).

Section 2 provides a concise overview of business model literature, followed by our research model in section 3. Section 4 details our methodology, and section 5 reports our results. Limitations are given in section 6, and section 7 subsumes our conclusions.

2 Literature overview

The business model concept originates from various fields, including e-business, strategy, supply chain management and information systems (Hedman and Kalling, 2003, Shafer, et al., 2005), mainly as a response to the need to explicate the value of ICT-driven innovations for organizations and users. Studying business models serves various purposes, such as understanding the elements and their relationships in a specific business domain; communicating and sharing this understanding to the outside world; using them as a foundation for change; measuring the performance of an organization; simulating and learning about e-business; experimenting with and assessing new business models; and changing and improving the current way of doing business (Osterwalder and Pigneur, 2002, Pateli and Giaglis, 2004). Since its conception, the field has developed from defining the concept, via exploring business model components and developing taxonomies of typical business models, to developing descriptive models (Pateli and Giaglis, 2004). While we are aware of the many discussions devoted to defining the concept (Alt and Zimmermann, 2001), we define a business model here as a blueprint for the way a business creates and captures value from new services or products (Chesbrough and Rosenbloom, 2002). As such, it describes the way a company or network of companies aims to make money and create consumer value (Faber, et al., 2003).

In our view, business models are an abstraction of how organizations create value (Seddon and Lewis, 2003). However, external factors like socio-economic trends, technological developments, and political and legal changes are important in understanding how business models are used in practice. With a few exceptions (Andries, et al., 2006, MacInnes, 2005, Vaccaro and Cohn, 2004), most literature has taken a static perspective on business models, implicitly assuming them to remain stable over time. However, in reality organizations often have to reinvent their business model continuously to keep aligned with fast-changing environments in some sectors (Afuah and Tucci, 2003). As a result, business models have to balanced during all phases from development to exploitation. Instantiations of business model dynamics may be found in any component of the business model, such as redefining or extending the service concept, adding or removing partners from the value network, replacing technologies, or adapting financial arrangements.

3 Research model

Phasing models help to understand how innovation and change impact firm strategies and business models (Afuah and Tucci, 2003). Phasing models have appeared in technical service development, entrepreneurial and business planning, innovation adoption and diffusion and marketing. As argued by Kijl et al. (2005), these models broadly imply three main phases: technology/R&D, implementation/roll-out, and market (the latter including sub-phases market offering, maturity, and decline). Although the phases suggest linearity, feedback loops may exist, e.g. when business models do not work out as planned. And when innovations are more successful than planned, some steps might more or less merge, obscuring the transition between the last two phases. The three phases are incorporated in the dynamic business model framework from Bouwman and MacInnes (2006). As this framework explicitly proposes links between external drivers and business model phases and has not yet been tested with quantitative data, it is usable for our present research purposes.

The first phase is dominated by R&D and technology. Discussions are focused at service or product definitions, investment in new technologies, and collaboration with relevant (technology) providers. The shift from Phase I to II is characterized by testing of concepts, small-scale roll out, field experiments, and initial introduction. In this phase roll-out of technology, testing of alpha and beta versions and embedding of the new technology in an organizational domain become more relevant. The service and supporting technology are not yet entirely developed and still open to changes and reconfiguration. Shifts in service definition or technology architecture can still occur, impacting the involved partners. First steps are made in marketing the service and gathering market data on customer acceptance. The shift from Phase II to III is characterized by focus on commercial exploitation. At this point, market experiments have proved successful and a critical mass of users is reached. The focus shifts from capturing markets to retention of market share. In the third phase, market adoption gradually spreads and day-to-day exploitation, operations, and maintenance are key activities.

We expect technology to be the most important driver in the first phase, as e.g. telecommunications networks enable increased reach of businesses while simultaneously middleware and multimedia applications offer new opportunities for enriched, customized, and secure communication. However, market developments and regulation can also trigger opportunities for the development of

new products and services, especially for more market-oriented firms or in less technology focused industries.
In the rollout phase the product or service must comply with regulation regarding issues as fair competition, telecommunication regulation, privacy, intellectual property rights, and content regulation. Regulators and competitors are becoming aware of the new product and services offered, and will look into possible implications for regulation as well as prepare a strategic response. New innovative technologies or alternative versions of existing applications can be incorporated. We assume that the effects of regulation are most decisive. Changes in marketing factors and technology can affect the service and business model, but with lower impact.
Due to the experiments in the roll-out phase, more information on market opportunities, technology operations, and user perception of ease of use, usefulness and utility potential are collected that impact the business model. Redefinition of service, involved parties and business models may take place as a result. With the roll-out of the service new partners might emerge, shifting the company from an R&D focus towards a more market oriented or commercial approach. Market know-how is a more important asset. Practical issues such as pricing, billing and possibly bundling with other services (and products), have to be solved.
In summary, we outline the following hypotheses, see Figure 1:

- H1: Technology drivers are most relevant in the Technology / R&D phase, decreasing to medium in the second and low in the third phase.
- H2: Market drivers are most relevant in the Market phase and less in phase II and I.
- H3: Regulation drivers are most important in the Implementation / Roll-out phase, and less in the first and third phase.

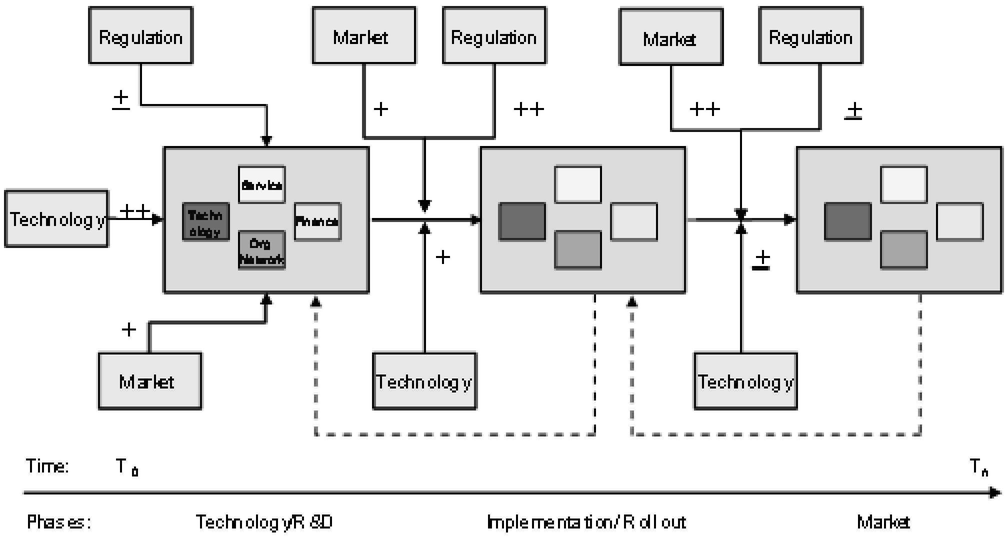

Figure 1: Dynamic business model framework (Bouwman & MacInnes, 2006)

We specify technology related drivers into general technology trends: digitization, processing power, miniaturization, mobile technology, technical integration, positioning technology, intelligent systems, interoperability, security, and natural interfaces (Bouwman, et al., 2005b). To this list we add Internet technology, standardization bodies, incremental nature of technology, and degree of technical sophistication. As market related drivers we consider Porter's forces of entry barriers, threat of substitution, suppliers' bargaining power, firms' rivalry (Porter, 1985), competitors' business models, vertical and horizontal integration, and financial and general innovation climate. Regarding the demand side of the market we see customers' income-level, unserved target groups, degree of customer power, Internet adoption, mobile adoption and a set of socio-economic trends, i.e. individualization, self-chosen collectivity, informalization, intensivitization, feminization, ageing of population, increasing cultural diversity (Idenburg, 2004). Regulation drivers are deregulation, regulation from national regulatory authority, economic regulation, legal regulation, security regulation, and customer protection regulation.

4 Method

As Yin and Heald (1975) argue, case surveys are particularly suited when a heterogeneous collection of case studies exists and researchers are interested in their characteristics rather than the authors' conclusions. The approach combines advantages of survey research and qualitative case studies, as it enables quantitative analyses and statistical generalizations, while capitalizing on the richness of case material (Larsson, 1993). We used content analysis as a tool. The present research is the final step in a three-stage research strategy, following two previous steps (Bouwman and MacInnes, 2006, Bouwman, et al., 2006) in which the framework was tested by qualitative studies of one and six cases respectively.

4.1 Case selection

We selected over sixty case descriptions on business models from companies as Abcam.com, Blockbuster, Centagenetix, Disney, NTT DoCoMo, Electronic Arts, FedEx, Google, Intel, Matsui, MySQL, Non-stop Yacht, Paypal, Cisco, Webraska and Yahoo!. To ensure comparability across cases, we used teaching cases as their structure is more or less similarly. In addition, they provide longitudinal descriptions required for testing the time dimension of our hypotheses, and they are readily available. For each case, descriptions were sourced from business school teaching cases developed between 1999 and 2004. Not all cases described all three phases of our research model, simply because the service had not reached mass market yet or as it concerned an established company already in the last phase. Other cases showed feedback loops going through phases multiple times. To solve this heterogeneity across cases, we decided to consider each phase of a case as a unit of analysis on its own. This resulted in 97 units of analysis.

Cases were selected from various industries to increase the applicability of our results, (Table 1). Most service concepts had an e-commerce component. We had about as much start-ups as established companies, as well as small and large companies. The division among phases is almost equal, although phase III is somewhat underrepresented.

Table 1: Case characteristics (n=97)

Variable	Category	Frequency
Industry sector	Mobile telecommunications	11
	Telecommunications	3
	Software	7
	Healthcare	7
	Consumer goods	13
	Finance	8
	Entertainment	11
	Intermediary services	26
	High-tech sector	1
	Logistics / Transport	10
E-commerce?	E-commerce	75
	Traditional business	9
	Missing	13
Nodal company age	Start-up	59
	Established	38
Nodal company size	Small (<150 employees)	57
	Large	40
Phase	I	36
	II	38
	III	23

4.2 Case study protocol

We developed a coding protocol specifying the variables to be coded (available upon request from the first author). Variables in the protocol were background variables (company size, age, strategy, culture, technology fit, industry sector, innovation type) and driver variables (see section 3). For the background variables, categorical scales were used. For each of the driver variables, we specified objective criteria to code the significance of the drivers on an ordinal scale, stretching from strong, weak, and questionable to absent influence. In addition to the pre-coded driver variables, we added free-format fields in the protocol to add other relevant drivers coders would find in the case description.

We developed a detailed manual, as is common in content analysis, on how to use the protocol, outlining each step that coders should take. It defined the rules how coders should distinguish the three phases. The start of phase I was defined simply as the moment first ideas about the service concepts or technologies were conceived. The shift from phase I to phase II was specified as the moment the service was launched on the market. To signal transition from phase II to III indicators were specified in the following order of importance: reaching critical mass; shift of focus from market expansion to customer retention; launch of version 1.0 of the service; and targeting new markets. In addition to the phasing, the protocol defined each variable in the protocol, or a reference to literature. Only information could be coded that was found in the case description. In case of uncertainty about the meaning of variables or values coders had to contact the principal authors.

4.3 Coding the cases

As multiple coders is essential for reliable case survey research (Larsson, 1993, Yin and Heald, 1975), we used four coders to analyze the cases. Each case was assigned randomly to two of the four. Coders had on average two cases to code every day. The first step in coding the cases was reading the material and deciding on the start and end dates of the phases of the case individually. Then, coders compared and discussed their perception of the phases, resulting in a shared phase definition, ensuring that both coders would use the same material. As we expected, defining feedback loops and shifts from the second to the third phase was most problematic. Then, coders individually coded the variables of the protocol. After coding all cases, we recoded the free-format driver variables into ordinal variables wherever possible.

4.4 Reliability

As we rely on observer interpretation, we had to compute intercoder reliability measures. Regarding external drivers, data indicated that coders mostly agreed whether a driver had been of any importance, but typically disagreed on the level of influence. Therefore, we recoded the external drivers to binary values, i.e. `influencing' and `no influence'. After this transformation, we found percent agreement among coders exceeding 70% for 62 out of 65 driver variables (94%) and for 4 out of 8 background variables. To correct for the probability that agreement may be due to chance, we computed Cohen's Kappa as well. However, we found that spread among the variables was typically low (many drivers were predominantly coded `no influence'), leading to disproportionately low Kappa values. For example, for some variables percent agreement was over 90 % while Kappa values were lower than 0.6. Therefore, we consider that for this type of data percent agreement can be used to measure intercoder reliability. We removed all variables with percent agreement lower than 70 %. As taking averages of two coders is impossible, we then selected one coding of each case and dropped the other, based on which coder generally scored better Kappa values.

5 Results

We grouped all drivers to aggregate measures for each of the three categories (i.e. technology, market and regulation). We calculated two types of aggregate measures: a ratio-scale variable summing the total number of lower-level drivers with value `influence' for the respective categories, and a binary variable coded `1' for cases with one or more of the low-level drivers coded `influence' and `0' when none of that type of drivers had been important for the case.

We found interaction effects between our background variables, which is relevant as we aim to relate them to our main findings later in this section. First, nodal company size relates to its age: start-ups are often small while established companies are large ($\chi2(1) = 53.62$, $p<0.001$). Second, company size is related to the industry sector: e-commerce companies are often small ($\chi2(1) = 5.82$, $p<0.05$). Third, there is a relation between nodal company age and industry sector: start-ups are more often in e-commerce ($\chi2(1) = 6.73$, $p<0.01$). In sum, start-ups are often small e-commerce companies, while established companies are often large companies in traditional sectors.

5.1 Technology drivers

Our first hypothesis is that technology drivers are most important in the first phase, decreasing to medium in the second and low in the third phase. We tested this by logistic regression analysis, using the binary aggregate technology driver variable as a dependent variable, and the phase variable as a predictor. The phase variable is recoded into two dummy variables with base value referring to phase I as we want to see if importance of the driver is lower in the other phases compared to phase I. We also executed linear regression analysis, taking the ratio-scale aggregate technology driver variable as a dependent. The results confirm our hypothesis that technology drivers are less important in later phases than in phase I (see Table 2 and 3).

Table 2: Logistic regression for binary technology driver

		95% CI for exp *b*		
	B (SE)	Lower	exp *b*	Upper
Constant	0.223 (0.335)		1.25	
Phase II (dummy)	-1.39** (0.508)	0.092	0.248	0.672
Phase III (dummy)	-2.575** (0.812)	0.015	0.076	0.375

Note: Hosmer & Lemeshow p-value = 1, R2 = .16 (Cox & Snell), .22 (Nagelkerke).
* p<.05; ** p<0.01; *** p<0.001.

Table 3: Linear regression for ratio-scale technology driver

	B	SE B	β
Constant	1.222	0.183	
Phase II (dummy)	-0.801	0.255	-.366**
Phase III (dummy)	-1.005	0.293	-.367***

Note: F = 7.4795, df = 94, 2, p≤0.001. R2 = .137. * p<.05; ** p<0.01; *** p<0.001.

We checked if results would be different for business size and business age (e-commerce and industry variable do not provide sufficient number of cases per category to do regression analyses). For the logistic regression analyses for small businesses the coefficient for phase II is significant, and that for phase III the coefficient is not (see Table 4). This can be explained as for none of the 16 cases of small businesses in phase III technology drivers are present (!).

Table 4: Logistic regression for binary technology driver, small businesses

		95% CI for exp *b*		
	B (SE)	Lower	exp *b*	Upper
Constant	0.288 (0.441)		1.333	
Phase II (dummy)	-2.134** (0.762)	0.027	0.118	0.527
Phase III (dummy)	-21.491 (10742.02)	0.000	0.000	0.000

Note: Hosmer & Lemeshow p-value = 1, R2 = .29 (Cox & Snell), .423 (Nagelkerke). * p<.05; ** p<0.01; *** p<0.001.

As for the large businesses, the model has much lower explained variance, and none of the coefficients are significant. Still, there is no significant relation between business size and amount of drivers found regardless of the phase ($\chi 2(1) = 2.02$, ns), so one cannot conclude that technology drivers are not important at all for these type of companies.

Table 5: Logistic regression for binary technology driver, large businesses

		95% CI for exp *b*		
	B (SE)	Lower	exp *b*	Upper
Constant	0.134 (0.518)		1.143	
Phase II (dummy)	-0.644 (0.731)	0.125	0.525	2.200
Phase III (dummy)	-1.386 (0.954)	0.039	0.250	1.623

Note: Hosmer & Lemeshow p-value = 1, R2 = .058 (Cox & Snell), .079 (Nagelkerke). * p<.05; ** p<0.01; *** p<0.001.

For start-up companies, we see a similar phenomenon as for small companies. Again, the same conclusions are drawn comparing phase I with phase II, but for phase III no start-ups are in the datasets, which obstructs making claims. And similar to the large businesses, we find again that the hypotheses are not confirmed for established businesses. We indeed find a relation between business age and technology drivers: $\chi2(1) = 4.69$, $p < 0.05$.

Table 6: Logistic regression for binary technology driver, startups

		95% CI for exp *b*		
	B (SE)	Lower	exp *b*	Upper
Constant	0.095 (0.437)		1.100	
Phase II (dummy)	-1.992** (0.758)	0.136	0.031	0.602
Phase III (dummy)	-21.298 (10377.78)	0.000	0.000	0.000

Note: Hosmer & Lemeshow p-value = 1, R2 = .26 (Cox & Snell), .39 (Nagelkerke). * p<.05; ** p<0.01; *** p<0.001.

Table 7: Logistic regression for binary technology driver, established companies

		95% CI for exp *b*		
	B (SE)	Lower	exp *b*	Upper
Constant	0.405 (0.527)		1.500	
Phase II (dummy)	-0.811 (0.745)	0.103	0.444	1.915
Phase III (dummy)	-1.504 (0.972)	0.033	0.222	1.493

Note: Hosmer & Lemeshow p-value = 1, R2 = .073 (Cox & Snell), .098 (Nagelkerke). * p<.05; ** p<0.01; *** p<0.001.

We find similar results (not displayed here) in linear regression analysis with the ratio-scale technology driver measure: the model fits better for the small, startup company cases, but no longer for the large, established companies.

In terms of our hypothesis, we find support as technology drivers are more important in phase I than in the other phases. However, the hypothesis only seems to apply to small startup cases.

5.2 Market drivers

Our hypothesis is that market drivers are most important in phase III, and less in phase II and I. Therefore, we construct two dummy predictor variables for the phase variable with base value phase III. From the results in Table 8, no significant difference appears in market driver importance when comparing phase II and I to phase III respectively.

Table 8: Logistic regression for binary market driver (base value = Phase III)

		95% CI for exp *b*		
	B (SE)	Lower	exp *b*	Upper
Constant	0.262 (0.421)		1.300	
Phase I (dummy)	0.990 (0.581)	0.862	2.692	8.409
Phase II (dummy)	-0.581 (0.534)	0.197	0.559	1.592

Note: Hosmer & Lemeshow p-value = 1, R2 = .10 (Cox & Snell), .13 (Nagelkerke). * p<.05; ** p<0.01; *** p<0.001.

However, when we take phase I as a reference (i.e. use dummy variables like in the Technology driver model), we find that there are significant differences in driver importance when comparing phase I to phase III, and an indication of a difference (although not significant) between phase I and II. So, the data suggests that our hypothesis is invalid, and rises an alternative hypothesis that market drivers are most prominent in phase I. The same alternative hypothesis is supported by the linear regression analysis of the ratio-measure for the market driver, see the table below.

Table 9: Logistic regression for binary market driver (base value = Phase I)

		95% CI for exp *b*		
	B (SE)	Lower	exp *b*	Upper
Constant	1.253** (0.401)		3.500	
Phase II (dummy)	-1.571 (0.518)	0.075	0.208	0.574
Phase III (dummy)	-0.990** (0.581)	0.119	0.371	1.160

Note: Hosmer & Lemeshow p-value = 1, R2 = .10 (Cox & Snell), .13 (Nagelkerke). * p<.05; ** p<0.01; *** p<0.001.

Table 10: Linear regression for ratio-scale market driver (base value = Phase I)

	B	SE B	β
Constant	0.652	0.264	
Phase II (dummy)	1.014	0.338	.368**
Phase III (dummy)	0.085	0.334	.801

Note: F = 6.568, df = 94, 2, p≤0.01 R2 = .123. * p<.05; ** p<0.01; *** p<0.001.

When splitting the output according to company size and age variables, we again find differences in model fit between the categories. We find remarkably higher explained variance, and more significant coefficients for small businesses and startups, see Table 11 and 12.

Table 11: Logistic regression for binary market driver, small businesses

		95% CI for exp *b*		
	B (SE)	Lower	exp *b*	Upper
Constant	1.792** (0.624)		6.000	
Phase II (dummy)	-2.351* (0.765)	0.021	0.095	0.427
Phase III (dummy)	-1.792** (0.821)	0.033	0.167	0.834

Note: Hosmer & Lemeshow p-value = 1, R2 = .192 (Cox & Snell), .258 (Nagelkerke). * p<.05; ** p<0.01; *** p<0.001.

Table 12: Logistic regression for binary market driver, startups

		95% CI for exp *b*		
	B (SE)	Lower	exp *b*	Upper
Constant	1.447** (0.556)		4.250	
Phase II (dummy)	-1.889** (0.701)	0.038	0.151	0.598
Phase III (dummy)	-1.580* (0.759)	0.046	0.206	0.912

Note: Hosmer & Lemeshow p-value = 1, R2 = .141 (Cox & Snell), .189 (Nagelkerke). * p<.05; ** p<0.01; *** p<0.001.

For the large and established businesses, the model does not fit, see Table 13 and 14. However, we find no significant relation between the drivers and business size ($\chi 2(1) = 0.04$, ns) nor business age ($\chi 2(1) = 0.50$, ns).

Table 13: Logistic regression for binary market driver, large businesses

		95% CI for exp *b*		
	B (SE)	Lower	exp *b*	Upper
Constant	0.693 (0.548)		2.000	
Phase II (dummy)	-0.693 (0.742)	0.117	0.500	2.139
Phase III (dummy)	0.000 (0.894)	0.173	1.000	5.772

Note: Hosmer & Lemeshow p-value = 1, R2 = .027 (Cox & Snell), .037 (Nagelkerke). * p<.05; ** p<0.01; *** p<0.001.

Table 14: Logistic regression for binary market driver, established businesses

		95% CI for exp *b*		
	B (SE)	Lower	exp *b*	Upper
Constant	1.012 (0.584)		2.750	
Phase II (dummy)	-1.145 (0.780)	0.069	0.318	1.468
Phase III (dummy)	0.087 (1.004)	0.153	1.091	7.802

Note: Hosmer & Lemeshow p-value = 1, R2 = .073 (Cox & Snell), .10 (Nagelkerke). * p<.05; ** p<0.01; *** p<0.001.

When testing the linear regression model based on the ratio-scale measure for aggregate market drivers, similar results are gained: explained variance and significance of coefficients increases for start-ups and small companies, while the model no longer fits for established, large companies.

In sum, we have to reject our initial hypothesis that market drivers are most important in the third phase, and advance alternatively that they are most relevant in the first phase. We again specify this hypothesis for small startups only.

5.3 Regulation drivers

The hypothesis for regulatory drivers is that they are most important in the second phase, and less in the first and third phase. However, neither binary logistic regression nor linear regression indicates any significant differences when comparing phases.

Table 15: Logistic regression for binary regulation driver

		95% CI for exp *b*		
	B (SE)	Lower	exp *b*	Upper
Constant	-1.887*** (0.480)		0.152	
Phase I (dummy)	0.634 (0.625)	0.554	1.886	6.423
Phase III (dummy)	0.606 (0.697)	0.468	1.833	7.187

Note: Hosmer & Lemeshow p-value = 1. R^2 = .01 (Cox & Snell), .02 (Nagelkerke). * $p<.05$; ** $p<0.01$; *** $p<0.001$.

Table 16: Linear regression for ratio-scale regulation driver

	B	SE B	β
Constant	0.132	0.090	
Phase I (dummy)	0.202	0.130	.175
Phase III (dummy)	0.173	0.147	.132

Note: F = 1.368, df = 94, 2, ns. R^2 = .028. * $p<.05$; ** $p<0.01$; *** $p<0.001$.

Differentiating between business size and age does not produce better models; with Nagelkerke R Square still lower than 0.05. Cross tabulations also do not indicate significant relations between the binary regulatory driver measure and business size ($\chi2(1) = 3.60$, ns) nor business age ($\chi2(1) = 4.46$, ns). So, we have to reject our hypothesis that regulation is most relevant in the second phase. Alternatively, we propose that regulation plays a minor role throughout all phases, regardless the company size and age.

6 Limitations

As in any case survey research, quality of our findings is constrained by the quality of the original case descriptions (Yin and Heald, 1975). The case material was collected for other purposes originally, and may have focused on specific fields of interest or educational purposes. However, we did find for example that technology drivers were mentioned contrary to what might be expected from business scholars. Besides, while data collection always risks interpretation and bias, using existing cases from different authors reduces risk of personal bias. The reason to use existing cases was that we wanted to test existing theory with other material than cases previously used for developing our model (Haaker, et al., 2006) and to allow for statistical generalizability that would have been infeasible when collecting primary data ourselves. Future case survey research may be improved by combining several types of case descriptions, i.e. both teaching cases and research cases, or by validating coding with company stakeholders (Larsson, 1993).

It was rather difficult to assign the right phasing to the cases; especially the transition from second to third phase is troublesome. In some cases we found contradictory indicators in the case descriptions. Much discussion was needed among the coders and researchers to reach agreement on transitions. This underlines the importance of strict operationalization of phasing models for similar future research.

While we constrained our coders to the information in the cases, we often found that from common sense one would feel that a driver is actually important but that it was not mentioned explicitly in the case description. In retrospect, we might better have given the coders more freedom to use their own interpretation, although that would have inevitably created bias towards more well-known cases.

7 Conclusions and discussion

The objective of the present paper was to find which external drivers are most relevant throughout the phases of a business model life cycle. Our study indicates that technology and market type of drivers are most relevant in the stages of service conceptualization and underlying technology development. For technology drivers, this was what we expected to find, but for market drivers it is contrary to our expectations. Apparently, decisions about new services and underlying technologies are more fueled by market developments than adjustments in these choices later on.

Surprisingly, we found very little cases in which regulation drivers play a role, merely 18% of all cases, and we did not find any relation between the phase in the life cycle and the importance of this type of drivers like we had expected. We propose alternatively that regulation plays only a minor role throughout all phases of a business model life cycle.

In terms of specifying our model, we found that it is much more applicable for business models centered on small, startup companies than it is for large, established businesses. Although external drivers are also important for larger, established companies developing new business models, the role of these drivers appears to be fairly equal over time.

Combining our findings leads to the adjusted research model in Figure 2.

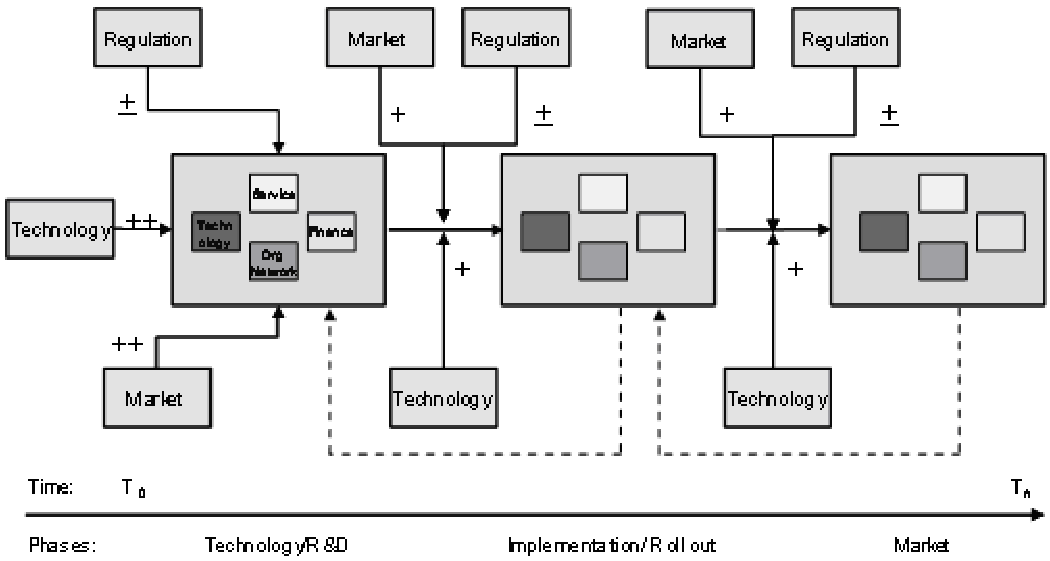

Figure 2: Adjusted dynamic business model framework for small startups

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