Supporting business model decisions: a scenario-based simulation approach

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Abstract: A key challenge for entrepreneurs is to find a robust and scalable business model. In complex environments, business model decisions often build on highly uncertain assumptions. The uncertainty increases when the entrepreneurial venture is confronted with unexpected changes in the environment. This paper proposes an approach to support entrepreneurs in understanding the future implications of their business model decisions. The approach combines system dynamics simulation modelling with formal scenario building. The paper presents a novel conceptual approach to modelling business models. It develops a business model simulation for a multi-sided platform such as the online marketplace eBay. The paper builds future scenarios to conduct simulation experiments that incorporate the uncertainty of developments external to the firm. Based on historic data of eBay, it demonstrates how the scenario-based simulation approach allows comparing the implications of different revenue model options on eBay’s performance. Finally, the research discusses the general applicability of the scenario-based simulation approach as a tool for entrepreneurial decision making.

Keywords: entrepreneurship; online marketplace; multi-sided platform; business model; network effects; computer modelling; system dynamics; eBay; internet startups; scenario building; high-growth firms; firm growth; decision support.
1 Introduction

With the advent of the new economy, business models have become an increasingly popular unit of analysis to explain differences in firms’ success (Afuah and Tucci, 2003). Business model research suggests that appropriate business models can lead to sustainable competitive advantage and superior financial performance (Zott and Amit, 2007). The business model concept describes the firm’s value proposition, how it creates, delivers and communicates this value, and how the firm captures value for itself from these activities (Abdelkafi et al., 2013). It has been considered as a layer between the firm’s strategic and operational layer (Osterwalder, 2004) and the output of a deliberate design process. Literature has strongly focused on describing and categorising business models; however, it still lacks approaches to operationalise the construct in a way that empowers entrepreneurs in making better business model decisions.

Take, for example, the decision of selecting an appropriate revenue model for a digital marketplace such as eBay. A digital marketplace is a special type of business model known as a multi-sided platform (MSP) that – per definition – connects two different market segments which value each other’s presence (Hagiu and Wright, 2015). For a traditional bricks-and-mortar-retailer, this decision would mostly refer to choosing a price premium. In a MSP, however, firms can generate revenues from more than one customer group. As such, a business like eBay can charge those users that are selling the goods and/or those users that are buying goods on the platform. In such cases, one customer segment might even be entirely subsidised; a pattern that has been described as ‘freemium business model’ (Osterwalder and Pigneur, 2010). Such key business model decisions are non-trivial since they generate a variety of consequences for the firm’s customers, partners, and the firm itself.

The implications of entrepreneurial business model decisions are systemic in nature. As such, the set of implications is often interdependent and therefore self-reinforcing over time. Judging the implication of a seemingly simple decision – which customer side pays for a service – will therefore have performance implications that cannot be anticipated intuitively. Sterman (2000) has shown that most humans generally lack the capability to even anticipate simple dynamics of complex systems. The predictability of these dynamics further decreases with the uncertainty about the venture’s environment.
Moreover, many entrepreneurs lack the instruments and approaches to gain a better understanding about the systemic cause-and-effect implications of their decisions. Thus, business model literature has motivated research to build business model tools and methods that build on systemic thinking (Täuscher and Abdelkafi, 2015).

This paper aims at developing and applying an approach for entrepreneurs to reduce uncertainty when making critical business model decisions. Therefore, the research is guided by the question: How can entrepreneurs systematically assess the implications of their business model decisions? The paper proposes an approach that combines the methodologies of simulation modelling with scenario development (Schoemaker, 1995). Scenario development is a method from strategic planning which aims at better understanding the future implications of today’s decisions. Rather than forecasting one exact future state, this method develops several potential future scenarios. A scenario describes either a possible reality of the future or the evolution of events over a period of time (Becker, 1983). Scenario building aims at increasing cognitive awareness, testing existing assumptions or developing better strategies to deal with a broader range of potential scenarios.

Scenario planning is well suited to support business model decision making for several reasons. The process of scenario building alone can reduce the cognitive bias of entrepreneurs and managers (Schoemaker, 1995). Entrepreneurs can easily develop a tunnel vision and over-confidence in the assumptions underlying their business model. New knowledge is subsequently often only absorbed to confirm existing assumptions (Kahneman, 2011). Scenario analysis has further proven a useful middle ground between over- and under-predicting the influence of certain external factors on the firm’s performance (Swart et al., 2004). In particular, it can include qualitative factors such as a change in regulations or technology – which are often ignored by purely quantitative approaches that focus on those factors that are easily measurable and are somehow predictable (Harris, 2014). Changing the mental models of decision makers, however, often requires a captivating story rather than extensive quantitative data. Therefore, scenario building has been suggested as perfectly complimentary to simulation modelling (Cavana, 2010).

We apply the simulation paradigm of system dynamics (Forrester, 1961; Sterman, 2000), which has been recognised as the ideal vehicle for modelling complex, dynamic systems. System dynamics provides a mature set of procedures for the structured development and validation of dynamic models (Schwaninger and Grösser, 2009). Besides, the underlying paradigm has been applied as a structural theory in different realms of management science (e.g., Größler et al., 2008). The paper applies the proposed approach to the complex business model type of digital marketplaces, a form of MSPs. The simulation of such business models is challenging due to a variety of self-reinforcing growth dynamics that need to be considered systemically (Eisenmann et al., 2007). Therefore, the paper specifically aims at providing practical insights on how to develop and conduct simulation experiments with business models of MSPs.

The paper is organised as follows: the following sections will review the relevant literature (Section 2), develop a system dynamics simulation model (Section 3), apply the scenario-based simulation approach to eBay (Section 4), discuss the findings (Section 5) and provide conclusions and an outlook on future research opportunities (Section 6).
2 Related literature

2.1 Business models

Business model literature has not converged towards a common definition of the concept (Zott et al., 2011). Over the last years, an increasing number of scholars have considered business models from a systems perspective (Abdelkafi and Täuscher, 2016). Consequently, a literature review by Zott et al. (2011) concludes that the business model provides a “system-level, holistic approach to explaining how firms ‘do business’” (p.1019). Business models have been conceptualised as complex and dynamic systems building on a variety of interrelated elements that change over time (Demil and Lecocq, 2010). Literature that follows such a systemic understanding of business models has studied their underlying self-reinforcing dynamics (Casadesus-Masanell and Ricart, 2010), studied how business model patterns support these reinforcing dynamics (Abdelkafi and Täuscher, 2014), and how certain reinforcing dynamics can weaken the robustness of a business model (Täuscher and Abdelkafi, 2015). These approaches have yielded new insights into how to conceptually understand the causal effects underlying business models.

Business model analysis can occur at three levels:

a. structured description of the elements of a business model by means of a template such as the ‘business model canvas’ (Osterwalder and Pigneur, 2010)

b. identification of patterns that describe generic configurations of a business model (e.g., Abdelkafi et al., 2013)

c. the representation of the dynamics and interdependencies of the business model by means of formal modelling approaches (e.g., Täuscher and Abdelkafi, 2015).

Among the modelling approaches, the notation of causal-loop diagramming has been identified as a suitable approach to better understand the implications of business model decisions (Eurich et al., 2014). Systemic modelling approaches are particularly valuable if the business model builds on a complex set of elements.

The business model is an important driver of an entrepreneurial firm’s performance (Zott and Amit, 2008). As such, scholars have been concerned with identifying success criteria for assessing the effectiveness of a business model design. Hamel (2000) proposes four criteria: efficiency in delivering value to the customer, uniqueness of the business model, fit among the elements of the business model, and the existence of design elements that enhance profit potential such as network effects or economies of scale. Amit and Zott (2001) identify four design themes for value creation of business models: novelty, efficiency, lock-in, and complementarities. Lock-in effects generally exist if the customer receives more value from an offering over time. A lock-in effect can occur, for instance, if the customer becomes highly accustomed with the firm’s website, builds positive relationships with other users or has invested significant resources to build a user profile. Casadesus-Masanell and Ricart (2010) argue that effective business model design is aligned with the firm’s strategic objectives, builds on mutually reinforcing elements that create virtuous cycles and is robust to changes in the environment. Täuscher and Abdelkafi (2015) find that business model design is robust if it builds on predictable components and valid assumptions, if it demonstrates low sensitivity to environmental dynamics and if it is adaptable in case of external shocks. Most of these
conceptualisations are directly in line with a systemic view on business models; however, they have not been operationalised yet.

2.2 Digital marketplaces

This paper applies the proposed methodology to the complex business model type of digital marketplaces. Marketplaces describe business models of firms that:

a. build on a technological platform
b. integrate at least two different user groups
c. provide some form of transaction between members of the two user sides
d. do not (primarily) trade goods or services themselves.

Marketplace business models build a triangular relationship between the marketplace provider (the focal firm), a supply and a demand side (Hagiu and Wright, 2015). The value of marketplaces consists in matching actors of both market sides (e.g., though price mechanisms), facilitating the execution of the transactions (e.g., payment or delivery services), and providing an institutional and regulatory framework for these commercial transactions (Bakos, 1997, 1998). Digital marketplaces provide these functions primarily via a digital channel such as a web-based platform.

Digital marketplaces are a specific form of MSPs. While the literature on marketplace business models is almost inexistent, economics and strategy research has yielded important insights into MSPs. There exists a large body of literature on platform competition (Eisenmann et al., 2007.), platform adoption (Hagiu, 2014) and price management (Evans et al., 2006; Hagiu, 2006; Gawer and Cusumano, 2008). The emerging literature of platform management particularly investigates the existence and strength of network effects as a key feature of MSPs and two-sided markets (Parker and van Alstyne, 2014; Rysman, 2004), user behaviour and users’ quality preferences (Hagiu, 2009) or the impact of different pricing strategies (Armstrong, 2006; Rochet and Tirole, 2006). Other scholars have applied models from competitive dynamics (Sun and Tse, 2007) to analyse the dynamics of markets with these characteristics. While the literature has developed theoretical models on how to determine strategic and pricing decisions for MSPs, there is a lack of approaches and tools that support entrepreneurs in making real-world decisions for such complex business models.

3 Simulating business models

The approach for developing a simulation model for marketplace business models is based on the methodology, principles and tools of system dynamics. System dynamics is a modelling and simulation paradigm rooted in systems thinking. It builds on the assumption that a system’s performance can be anticipated by studying its cause-and-effect structure. System dynamics focuses on identifying nonlinear causal relations in a system. Empirical studies have shown that humans are generally incapable of anticipating the performance of a nonlinear system intuitively (Sterman, 2000). Hence, when applied to business models, system dynamics focuses on featuring the nonlinear dynamics which lead to feedback loops. A feedback loop exists if the value change of one
variable leads to a stronger change of the same variable in the next period. Within the last 50 years, system dynamics literature has developed a repository of methods, tools and partial models that facilitate the development of new simulation models and provides a good basis for practitioners. To develop a system dynamics simulation model, we follow the methodology by Sterman (2000) which centres around five key phases:

1. problem articulation
2. formulating dynamic hypotheses and causal modelling
3. developing a simulation model
4. running simulation experiments
5. decision making.

This section follows steps one to three, while the next section will show simulation experiments and how they serve as a basis for decision making.

### 3.1 Problem articulation

A key business model decision for marketplaces relates to the selection of an effective revenue model. The revenue model refers primarily to the type of revenue streams the company aims to generate (Osterwalder and Pigneur, 2010). The challenge of finding a revenue model in marketplaces or MSPs has been investigated theoretically by several scholars (Jullien, 2004, Parker and van Alstyne, 2005, Rochet and Tirole, 2006; Hagiu, 2006). Firms can charge:

1. a *commission fee* as a percentage of the transaction value
2. a *listing fee* as a fixed cost to sellers for publishing an offering
3. a *subscription fee* as a fixed fee per time period for access to the marketplace.

Each of these revenue model options has multiple effects on other components of the business model. Charging a transaction-dependent fee will result in fewer transactions. Charging a listing fee will reduce the amount of listings on the platform. Charging a fee for accessing to the marketplace will lead to fewer users joining the platform. While the listings fee can only be applied to the seller side, commission and subscription fees can be charged from seller and/or buyer side. Charging either one of these sides will have important implications on the user adoption of the marketplace. Thus, deciding on a revenue model is difficult because the interdependencies can lead to several reinforcing and balancing feedback loops. Besides, the decision depends on various external parameters such as the price sensitivity of each customer side. The model therefore aims at developing a simulation model of marketplaces to support revenue model options.

### 3.2 Building causal loop diagrams

The literature suggests that marketplace business models – as a type of MSPs – grow due to different self-reinforcing dynamics. Therefore, the model strives to capture the essential reinforcing feedback loops. Based on the review literature in the previous section, we identify three main self-reinforcing loops: network externalities, lock-in effect, and economies of scale.
3.2.1 Network externalities

Positive network externalities are a key characteristic of MSPs (Katz and Shapiro, 1994). One customer side’s value depends on the network size of the other side (Rysman, 2009). Nevertheless, network externalities have rarely been operationalised in formal models. Economides (1996) represents network externalities with a network modelling approach. Witt (1997) develops a system of differential equations to model network externalities. Thun et al. (2000) apply system dynamics to create a diffusion model with network externalities.

Figure 1 depicts how the model captures this effect. The number of buyers has a direct impact on the attractiveness from network size to sellers, which influences the marketplace’s value to sellers. The value to sellers has, in turn, a positive impact on the number of sellers and the number of listings due to more items listed per person. Note that in the full causal model, the link between value to sellers and sellers is rather indirectly represented via the impact on member acquisition and retention. Figure 1 further shows how the number of sellers and listings positively influences the attractiveness of network to buyers. This creates more platform value to buyers and subsequently leads to an increase in buyers on the marketplace.

**Figure 1** Network externalities (see online version for colours)

![Network externalities diagram](image)

3.2.2 Lock-in effect

A second reinforcing feedback loop is not available initially, but unfolds over time as the customer makes use of the marketplace. The more successful transactions users conduct via the marketplace, the more value they will receive from platform participation over time. The increased value refers to the value customers receive by acquainting themselves with the functionality of the platform, optimising their strategies for selling/buying via the marketplace, or building up a reputation via the amount of positive reviews from transaction partners. The increase in platform value to buyers/sellers leads to a decrease in churn of existing users and increased adoption of buyers/sellers. The increase in adoption can be explained through an increase in platform recommendations from loyal users to their networks due to the increased incentive to promote general
adoption of this particular platform. We label this feedback loop *lock-in effect*, which is in line with existing business model literature (Amit and Zott, 2001). This loop is theoretically supported by a broad range of empirical research that has collected transaction data on marketplaces similar to eBay. Existing research has validated that, among others, sellers receive more value from eBay the more positive transaction reviews they have already earned (Melnik and Alm, 2002; Houser and Wooders, 2006; Resnick et al., 2006). Figure 2 depicts the underlying logic of the lock-in effect. Since the effect equally applies to buyers and sellers, we show them simultaneously. In the model however, the lock-in effect for buyers and sellers is modelled separately to account for the differences in effect size.

**Figure 2**  Lock-in effect (see online version for colours)

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### 3.2.3 Economies of scale

Due to the model’s purpose, we do not focus on the dynamics of specific operational resources such as employees. However, a key characteristic of software-based firms is the existence of economies of scale. The initial development of the technological platform is highly cost-intensive (Eisenmann, 2006). However, firms such as eBay can generally expand their capacity at relatively low costs to serve millions of customers. Economies of scale arise in marketplaces when the average cost per unit or transaction decreases with increasing scale of operation (Bakos, 1991; Hagiu and Wright, 2015). Figure 3 depicts how the number of *successful transactions* fuels an increase in commissions, leading to higher *revenues* and subsequently larger *profits*. An increase in *profits* leads to a higher *investment budget* can serve as a source for *investment in value creation*. Investments in value creation include, among others, hardware purchases to increase data storage capacity, the acquisition of another business with a highly efficient technology, or the automation of service-intensive processes. The increase in value creation capacity allows the marketplace to host more transactions on its platform. At the same time, the investment in value creation has a balancing effect on the firm’s profits. Profits that are
invested are not captured by the firm. Therefore, the *economies of scale* loop will only have a growth-supporting effect as long as the gains in additional revenue from larger platform capacity exceed the associated investment costs.

**Figure 3** Economies of scale (see online version for colours)

*Figure 4* Interdependence between reinforcing dynamics (see online version for colours)
The three types of reinforcing feedback loops are not independent from each other. Figure 4 reveals how the economies of scale relate to the network externalities and lock-in effects to buyers and sellers. Network externalities to buyers (R1) and network externalities to sellers (R2) lead to an increase in buyers, sellers, listings and ultimately successful transactions over time. The more successful transactions are conducted by buyers/sellers, the stronger becomes the value from lock-in. These effects are captured in lock-in effect to buyers (R3) and lock-in effect to sellers (R4). Moreover, more transactions on the marketplace lead to decreasing costs per transaction due to economies of scale (R5) in the expansion of platform capacity. Figure 5 demonstrates that the three reinforcing dynamics are primarily connected via the number of successful transactions. An increase in successful transaction in one period will thus lead to an increase in transactions in the next period, as long as the loops remain their reinforcing nature.

As argued above, the causal model has to reflect the trade-off related to charging customers a fee. Since fees represent a price to use the marketplace service, they directly influence the platform value to these user segments. As a consequence, revenues are subject to a balancing effect. An increase in prices will lead to increased revenues, but at the same time reduce the value to users, which reduces the number and activity of users, leading to less transactions and, ultimately, to less revenues. Overall, the conceptual model represents and integrates these different reinforcing and balancing loops.

3.3 Developing the simulation model

To build the simulation model based on the theoretically identified feedback loops, we create reference diagrams for the identified key variables. We then develop a boundary table to explore which variables were endogenous or exogenous to the model. Next, we specify the units and dimensions for each of the variables to check for dimensional consistency. Subsequently, we specify the parameters and look-up tables with estimated data to test the model’s sensitivity to key variables. We adjust the model to increase or decrease the sensitivity to these variables and test the behavioural validity of the model (we provide more information on validity tests in the next section). While the simulation model cannot be fully documented in this paper, we will focus on how the simulation model solves three key challenges of formally modelling business models: modelling value to customers, customer adoption, and competing value propositions.

3.3.1 Value to customers

A key element of multi-sided business models is the fact that they offer (at least) two separate value propositions to the different customers sides (Muzellec et al., 2015). We therefore choose to model two different value functions for sellers and buyers. Value can be understood as the perceived utility to customers of experiencing the firm’s products or services. A business has to provide a positive net value to attract and retain customers. Users generally receive value from a business:

a. if it provides more efficiency in solving the ‘job-to-be-done’

b. if the process of interacting with the business itself provides value due to its novelty.
These two constructs – efficiency and novelty – are based on the framework of value drivers of entrepreneurial business models by Amit and Zott (2001). The same authors have developed and validated conceptual scales to measure efficiency and novelty for internet-based business models (2007, 2008). The core sub-module of the value to sellers is depicted in Figure 5.

Figure 5  Sub-module ‘value to sellers’ (see online version for colours)

3.3.2 Competing value propositions

The business model as a unit of analysis does not, per se, focus on competitive dynamics or questions of competitive differentiation (opposed to the firm’s strategy; Porter, 1985). Yet, business models do not function in isolation (Casadesus-Masanell and Ricart, 2013). The perceived novelty and efficiency – identified as key value drivers of business models by Zott and Amit (2001) – of a business model depend on the point of comparison. In the perception of customers, the first digital marketplace provided a high novelty compared to existing solutions such as physical marketplaces. Today, however, a digital marketplace per se does not provide any novel customer experience. Thus, we model these value drivers as relative to competing solutions. In the case of a digital marketplace, competing solutions can include other digital marketplaces, large online retailers, physical service providers, etc. Since efficiency and novelty are relative concepts – measured against other alternatives – we introduce an average value for the novelty and efficiency of competitive solutions. These variables are dimensionless and drawn from a randomised normal distribution with mean 1.2. The randomisation serves to capture the fact that these components are outside the firm’s control and cannot be predicted in a reliable manner. Every quarter, a new random value will be assigned for each of these relative values. This captures the idea that other firms will compete on these core value
drivers which would thus change the values of the relative variables. Moreover, the importance of efficiency and novelty differs between target customer segments. We therefore introduce variables that capture the *importance of novelty/efficiency to buyers/sellers* as a weighting factor. The value also depends on the price advantage of the marketplace against other competitive alternatives. The value to sellers contains the ‘value from network size to sellers’ as well as the value from ‘lock-in effect to sellers’. The sub-module for representing the ‘platform value to buyers’ is developed similarly to the seller module.

**Figure 6** Sub-module ‘user adoption’ (see online version for colours)

3.3.3 User adoption

To model the flows of user adoption, we use the diffusion model by Bass (1969). The Bass model incorporates two effects that drive the adoption of new users: word-of-mouth (WOM) and market saturation. As the concept of spread by WOM and advertisement are easy to understand and extensively discussed in the literature, they are not discussed in detail here (view, for example, Mahajan et al., 1990; Radas, 2006). According to the nature of internet-based ventures, we label the loop as viral loop (Eisenmann, 2006). The growth rate of the WOM loop slows down as a larger share of the potential market has already been penetrated. This balancing loop has been labelled market saturation. Since
the number of potential users is limited, a marketplace cannot endlessly attract new potential users. For simplicity, in this model, it is assumed that marketplace users that abandon the service will be lost as customers and do not return to the potential population. Therefore, customers that abandon the marketplace (churn) will do so without becoming potential users. Some marketplaces have distinctive acquisition models for the buyer and seller side. This sub-module is, however, specified for marketplaces in which members can act as buyers and/or sellers. In particular, it represents a consumer-to-consumer (C2C) model, where private individuals sell and buy products. The sub-module is represented in Figure 6.

Apart from the user base, the simulation model is characterised by a second stock: the listings. The listings stock is a function of the number of sellers multiplied by a constant variable called average listings per seller. The listings stock depletes at listing expiry rate. The listing expiry rate is the rate at which listings are cleared from the platform that have either been sold successfully or have been unsuccessfully presented on the platform for a certain amount of time. Subsequently, the outflow rate is it calculated as:

1. the sum of the number of successful transactions divided by a time constant
2. the difference between listings and successful transactions (representing unsold listings) multiplied by a list retirement rate (a rate at which old items are taken off the platform).

Both stocks and their related flows influence all sub-modules. The value to seller, depicted in Figure 5, indirectly depends on the user adoption and churn rate and the listing expiry rate. The choice to abstain from modelling further stocks – such as server capacity or employees – is driven by the abstracted nature of the business model perspective.

4 Applying the approach to eBay’s business model

This section seeks to apply the scenario-based simulation approach to the digital marketplace eBay in its entrepreneurial phase. The approach is applied retrospectively to analyse the early challenges of eBay. This approach has the advantage of testing the fit of the simulation with real-world data. EBay Inc. was founded in 1995 by Pierre Omidyar as a platform enabling private users to sell and buy goods online. During the first two years, Omidyar and his team further developed the value proposition to both market sides (Burnett and Schill, 1999). EBay is an interesting application case since it has pioneered the auction-based marketplace model and has sustained its success already for 20 years. The fictional analysis is situated in mid-1998, three years after the venture had been founded. During that time, the entrepreneurial venture’s main focus was on increasing the number of users on the platform to gain a sustainable competitive advantage as the world’s largest selection of goods listed for sale (Casadesus-Masanell and Thaker, 2012). However, different uncertainties regarding eBay’s environment were threatening the effectiveness of its business model.
4.1 Adapting the generic simulation model to eBay

To adapt the generic model to eBay, we follow the process of simulation modelling as described by Sterman (2000). First, we specify the model’s purpose. So far, eBay had charged only their seller side. Sellers on eBay had to pay a listing fee for publishing an item on the platform as well as a commission fee for successfully conducting a transaction. The purpose of the scenario-based simulation is to compare the potential implications of different revenue models on eBay’s growth performance. The timeframe of the analysis is defined as ten quarters, which represents a realistic timeframe to observe unexpected dynamics. We choose to model the company on a quarterly basis because the firm had to report its financials with this frequency. Since our interest is in exploring the general applicability of the model and scenario-based simulation experiments, we do not include specific business model adaptations or mergers and acquisitions (e.g., PayPal), or expansions into specific other product categories that occurred during that time. This approach is in line with Oliva et al. (2003). The entire scenario-based simulation support the business model decision: Should eBay have installed a different revenue model in 1998?

| Table 1 | Revenue model options |
|------------------------------------------|
| Seller commission fee | Seller listing fee | Buyer commission fee |
| Revenue model 1 (sellers) | 5% | $2.5/listing | - |
| Revenue model 2 (sellers and buyers) | 3% | $2.5/listing | 3% |
| Revenue model 3 (buyers) | - | - | 5% |

At the time, eBay used a revenue model that only charged the seller side with a fixed fee for posting a product offering on the marketplace (listing fee) as well as a fixed percentage of the product price (commission fee) for successfully conducted transactions. The listing and commission fees were differentiated in relation to the product price (the commission rate generally decreased with increasing price levels). Based on weighted average, we assume a listing fee of $2.5 and commission fee of 5%. We compare this existing revenue model 1 (RM1) with two alternative revenue models. As depicted in Table 1, revenue model 2 (RM2) charges both sellers and buyers with a commission fee of 3%, while maintaining the listing fee for sellers. Revenue model 3 (RM3) completely subsidises the seller side and only charges the buyer side with a commission fee of 5%.

The simulation model’s variables are calibrated with publicly available data. We use data from 1997 as training data for the model. For some variables – for instance the look-up tables for price sensitivity – we use best estimates based on available data. The model structure is not changed from the generic model since it is already developed for the business model of digital marketplaces in which individual users buy and sell products.

Throughout the model creation and calibration, we test for validity. Since the simulation model is a causative descriptive model, the validity of the internal structure of the model is as important as the validity of the output. Issues of autocorrelation and multi-collinearity in system dynamics models make it difficult to use statistical tests for validation for the model (Barlas, 1996). The validation follows the methods suggested by Forrester and Senge (1980) and Barlas (1996). Numerical parameter verification is based on published documents about eBay (see Forrester and Senge, 1980). For instance,
eBay’s revenue in the fourth quarter of 1997 was 5.74 million while the model suggests 5.11 million for that quarter. Next, an extreme-conditions test is conducted to check for flaws in the model structure and pertinent omissions in the model. This test is conducted by stressing the model with extreme conditions. Structure-oriented behaviour tests aim at analysing the sensitivity of the model to changes in parameter values (Sterman, 2000). These tests result in plausible model behaviour.

**Figure 7** Base case compared to actual data (see online version for colours)

Notes: Blue line: simulation model. Green line/red line: eBay’s historic performance.

Next, we conduct behaviour pattern experiments to test whether the model is capable of replicating major behaviour patterns exhibited in the real system. Parameters are estimated on the basis of the data from 1997. The data from 1998 and 1999 is used as a validation set, which is compared to the ex-post forecast from the model. The forecast data is an unweighted average of five simulation runs to reduce the noise from the randomly generated variables. Data for eBay’s historic performance is extracted from quarterly financial reports. Figure 7 compares the simulated and actual data for the member base (eBay’s customers) and product listings for the ten quarters starting in the third quarter of 1997. The range of tests described above assures the validity of the model structure and its behaviour validity.

### 4.2 Building scenarios

Next, we aim at designing plausible and consistent scenarios. As suggested by Schoemaker (1995), the user first identifies drivers of change in the firm’s environment. External factors influencing the performance of business models have been categorised within the three dimensions of: market, technology and regulation (De Reuver et al., 2010). Examples of external factors include changes in user requirements, the development of a disruptive technology that substitutes the firm’s offering or a new law prohibiting a specific technology. For each identified driver of change, at least one basic trend should be documented (Schoemaker, 1995).

The assumptions about eBay’s drivers of change and basic trends are made on the basis of documents from the respective time period. They are, however, rather used for illustrative purposes. A first driver is the adoption of the internet by the general population. The second driver relates to new internet technologies that bring electronic commerce from a niche to a mass market. A third driver of change relates to regulations on electronic commerce between individuals. The fourth driver of change is a shift in the role of consumers towards becoming producers themselves. Lastly, we include the
emergence of new business models – empowered by new needs and technologies – as a key driver of change. Table 2 illustrates basic trends – as perceived in 1997 – in regards to these drivers of change.

Table 2  Basic trends in 1997 related to eBay’s business model

<table>
<thead>
<tr>
<th>Trend</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trend 1</td>
<td>Internet usage will become much more available and convenient to users. A majority of the population will adopt the internet (Hamilton, 1997).</td>
</tr>
<tr>
<td>Trend 2</td>
<td>New internet security technologies will increase the level of trust in electronic commerce (Hamilton, 1997).</td>
</tr>
<tr>
<td>Trend 3</td>
<td>New regulation will make the internet a reliable institutional environment trusted by its users (Hamilton, 1997).</td>
</tr>
<tr>
<td>Trend 4</td>
<td>Brand names continue to decline in value. Non-branded individuals can become trusted commerce partners (Schoemaker, 1995).</td>
</tr>
<tr>
<td>Trend 5</td>
<td>New business models will emerge from internet-based companies (Schoemaker, 1995).</td>
</tr>
</tbody>
</table>

Schoemaker (1995) suggests to consequently identify key uncertainties. Key uncertainties describe areas with uncertain outcomes that will significantly affect the identified drivers of change. For building scenarios relevant to eBay, we transform each of the basic trends into a key uncertainty:

1. Will internet adoption continue to rise at the same growth rate?
2. Will buyers receive more value from digital marketplaces compared to traditional retailers?
3. Will internet users become over time less price sensitive to fees incurred by internet firms?
4. Can technological advancements continue to improve value creation efficiency of internet firms?
5. Will competitors provide more novel solutions than digital marketplaces in the near future?

Next, we build three scenarios for the basic trends and the related uncertainties. Schoemaker (1995) suggests to start with a best and worst case scenario. It is, however, likely that these extreme scenarios are neither plausible nor consistent. Scenarios should therefore be adjusted and added until the entrepreneurial team has developed three to five plausible, consistent and independent scenarios. The output of the scenario building process is a description of three to five scenarios and a visual representation of the uncertainty components for each of the scenarios. For eBay, we design a best case and worst case scenario by assuming that all uncertainties would develop either positively or negatively. We then refine the best case, worst case and a base case towards three plausible and consistent scenarios.

4.2.1 Scenario 1: e-commerce boost

Scenario 1 describes a future in which internet adoption increases rapidly around the world. Digital marketplaces become widely accepted by the mass market and – due to favourable regulations – provide a highly efficient alternative to retailers. Due to advances in internet security and further trust of e-commerce, users become more
acquainted to paying for internet services and therefore become less price sensitive to
platform fees. Technological advancements in web technologies and server performance
increase the efficiency of digital platforms by leaps. Attempts of established retailers to
create innovative solutions fail due to the momentum of peer-to-peer commerce.

4.2.2 Scenario 2: steady e-commerce growth
Globalisation spurs the adoption of internet use in many parts of the world. The idea of
buying and selling on digital marketplaces increasingly gains traction. Technological
advancements parallels internet growth, but there are no significant technological leaps
that would increase the efficiency of e-commerce compared to traditional retailers. As
more marketplaces emerge, they start competing on price. Some marketplaces offer their
services entirely for free.

4.2.3 Scenario 3: e-commerce bust
Internet adoption increases rapidly for a while. At the same time, technological
advancements slow down. The number of new users cannot be sufficiently served
through the existing infrastructure. As a consequence, e-commerce sites are not efficient
at all due to their slow loading times. E-commerce develops towards a niche market,
while the initial ‘hype’ of the internet slowly disappears without having changed
consumers’ buying behaviour. Due to increasing levels of cyber criminality, consumers
lose trust in other individuals and prefer buying from trustworthy retailers. New
regulations force digital marketplaces to pay taxes on transactions, which indirectly
increase the cost to buyers and sellers. This increases their value compared to traditional
retailers. Competition from other marketplaces is low, but there is a lack of technological
innovation in making digital marketplaces more efficient.

Table 3  Changes in key uncertainties per quarter

<table>
<thead>
<tr>
<th>Parameter assumptions for each of the scenarios (quarterly change)</th>
<th>E-commerce boom</th>
<th>Steady e-commerce growth</th>
<th>E-commerce bust</th>
</tr>
</thead>
<tbody>
<tr>
<td>Potential users</td>
<td>+50%</td>
<td>+10%</td>
<td>-20%</td>
</tr>
<tr>
<td>Relative efficiency to users</td>
<td>+20%</td>
<td>0%</td>
<td>-20%</td>
</tr>
<tr>
<td>Relative cost advantage</td>
<td>+20%</td>
<td>0%</td>
<td>-20%</td>
</tr>
<tr>
<td>Price sensitivity</td>
<td>-20%</td>
<td>0%</td>
<td>+20%</td>
</tr>
<tr>
<td>Relative novelty to users</td>
<td>+20%</td>
<td>0%</td>
<td>-20%</td>
</tr>
</tbody>
</table>

Each of these scenarios leads to different quantitative values for the identified key
uncertainties. Table 3 represents the assumptions regarding the parameter that relate to
the five key uncertainties. Consequently, we calibrate the model for each of the three
scenarios and experiment with the three different revenue models in each of the
scenarios.

4.3 Conducting simulation experiments
For each scenario and revenue model (RM), we conduct five simulation runs and
calculate an unweighted average. This reduces the effect introduced by pure randomness
since the model builds on several random elements (e.g., relative price advantage). Most importantly, all three revenue models lead to an S-shaped growth curve in scenarios 1 and 2. The results suggest that in scenario 1 – e-commerce boom – all three revenue models perform similarly, providing about 350 million dollars in the tenth quarter. In that scenario, RM2 (seller and buyer pay) is slightly superior to the other two revenue models. In scenario two, growth is much flatter in all three revenue models. However, RM1 (seller pay) is significantly superior to the two other scenarios, as depicted in Figure 8, yielding 250 million dollars of revenues in the tenth quarter. In scenario 3 – the e-commerce bust – eBay experiences a decrease in growth rates within the 10 quarters of analysis. In the e-commerce bust scenario, RM2 (both pay) is slightly superior to the others.

**Figure 8** Revenue growth for scenario 2 (see online version for colours)

The model allows obtaining further insights into the development of the parameters. For RM2 – which charges both buyers and sellers – we observe that the majority of potential internet users have been acquired by eBay, but many of them have already abandoned the service due to the fees. What’s more, the activity levels of buyers and sellers decrease in comparison to RM1 and RM3 due to a smaller lock-in effect of existing users.

The illustrative scenarios and revenue models suggest that RM2 would lead to superior performance in two of the three scenarios (1 and 3). However, the performance of RM2 is only slightly superior to those of RM1 and RM3 in these scenarios. In scenario 2, however, RM1 leads to a much better performance than RM2. Considering all three scenarios, the simulation experiments suggest that RM1 would – on average – lead to the highest performance. Thus, the simulation experiments suggest that eBay’s entrepreneurs should prefer RM1 over the competing alternatives. In conclusion, the simulation scenario-based simulation confirms eBay’s decision to only charge the seller side.

### 5 Discussion and implications

The simulation model demonstrates exponential growth behaviour for most of the scenarios and configurations. This is plausible since the model deliberately captures self-reinforcing dynamics of marketplace business models. This behaviour is in line with
Supporting business model decisions

theory on the growth trajectories of MSPs (Parker and van Alstyne, 2014). Exponential growth, however, does not last forever since all resources (e.g., potential user population) are finite (Schwaninger and Grösser, 2009). Due to the selected timeframe of ten quarters (January 1997 to July 1999), the simulation runs can already show the transition from exponential to non-exponential growth. The decline in growth rates is primarily driven by the limited stock of potential users. Per design, the simulation model does not increase the number of potential users. In practice, eBay has expanded into further geographic markets and product categories. This allowed the firm to discretely increase the stock of potential customers and therefore maintain their exponential growth rate. Since the simulation model does not capture such dynamics, the fit between the simulated and actual number of users decreases over time. Nevertheless, the general model behaviour still corresponds to the actual firm performance.

The simulation runs of eBay suggest that completely subsidising the buyer side leads to the best revenue performance in the observed timeframe. These simulation results depend, however, on a number of assumptions. For instance, the decision for a revenue model is highly dependent on the buyers’ and sellers’ price sensitivity. In the developed simulation model, revenues are more sensitive to the price sensitivity of buyers and sellers than to network externalities. This finding seems plausible since the positive network externalities only affect the revenues indirectly.

The simulation model does not fully reveal the fragility of marketplace business models. In practice, MSPs can fail due to a number of different causes. For instance, a big threat stems from so-called ‘platform envelopment’, which describes the launch of an established platform into an adjacent market (Parker and van Alstyle, 2014). The superior network size of a different platform can result in a shift of users from one platform to another in a short period of time. For the chosen unit of analysis – business models – the entrance of a large competitor is beyond the model purpose since business models focus on the inner functioning of one firm, rather than competitive dynamics. For entrepreneurs building a MSP, the threat of large competitors entering the market remains, however, relevant in the decision-making process. While the simulation model can be adjusted in terms of relative price advantage, relative novelty and relative efficiency, it does not directly incorporate the possible entrance of a larger network. However, the process of building possible scenarios can increase the awareness for such events that are outside of the model’s boundaries.

The applied combination of scenario building and simulation modelling is in line with the specific entrepreneurial challenges. First, entrepreneurs and their ventures are generally constrained by limited time and financial resources. Utilising existing partial models seems an appropriate strategy to minimise the necessary time and resources for model building. Still, building a comprehensive simulation model that fully accounts for competitive dynamics, macro-economic developments, or consumer trends is rarely an option. Making decisions at the business model level requires a systemic and holistic understanding of the firm’s underlying logic of value creation and capture over time. We therefore suggest that a tool to support complex business model decisions at the entrepreneurial level should focus on important dynamics of value creation and user adoption rather than flows at an operational level. Designing abstracted models with latent constructs such as ‘value’ will, however, limit their predictive power. Second, entrepreneurs cannot comprehensively anticipate the future events that will affect their venture’s performance – such as the entrance of a new competitor. Combining simulation
modelling with the qualitative process of scenario building helps developing an understanding about the future’s uncertainty. Scenario analysis has been proven a useful tool for making more balanced and robust decisions. Consequently, the proposed process can trigger a shift in the mental models of entrepreneurial teams. By building and implementing the scenarios in the simulation model, entrepreneurs challenge or reinforce their understanding of their business model’s cause-and-effect relationships and its dependence on events outside the firm’s control. Thus, we suggest that the process of building scenarios and simulation experiments can have a superior impact on the entrepreneurs’ cognitive models then the quantitative simulation results itself.

6 Conclusions and directions for further research

The paper proposes an approach to support business model decisions in complex and uncertain environments. The approach combines the advantages of the rather qualitative and descriptive approach of scenario building with the data-generating approach of computer simulation. The approach enables entrepreneurs and managers to gain awareness about the uncertainty of their business model assumptions and the dependency of business model implications on developments that are outside the firm’s control. Therefore, the scenario-based simulation process serves as a stimulus for questioning existing mental models. To confirm the proposed impact of scenario-based simulation modelling on entrepreneurial cognition, further research should conduct a controlled study among entrepreneurial teams applying the approach.

This paper is the first to build a calibrated simulation model of the complex business model type of digital marketplaces. As such, it is a contribution towards integrating several theoretical constructs such as network effects and the lock-in effect in a practitioner-oriented form. The formal validation process and the comparison of the model behaviour with eBay’s historic data have demonstrated the model quality. However, as a system dynamics simulation model should never be considered as complete, further research can extend the model. For instance, the current model does not include the venture capital market. Since many entrepreneurial firms depend on external financing to support their rapid growth, the availability of venture capital has an impact on their business model decisions. The model could incorporate different revenue model options that have not been considered so far (e.g., selling customer data). Besides, the model could be further validated in workshops with entrepreneurs and managers of digital marketplaces.

Further research can adapt the simulation model for different research questions and business model types. The developed simulation model is deliberately designed in a generic way that is not specific to eBay or any individual firm. The simulation model could, for example, be adapted to other digital marketplaces that are not focused on products, but rather services (e.g., platforms for hospitality services). The calibration of the model to other businesses models can yield important insights into the key growth drivers of each business model type. Besides, running and comparing the model for marketplaces in different stages of their development can yield valuable hypotheses about the self-reinforcing growth dynamics, help identify the critical mass of platform users and give insights on general strategies for sustainable growth. Future research should aim at translating the simulation-based findings for such complex business models into actionable heuristics that can be applied by entrepreneurs.
References


