

Virtual Economies: Research Tools for Economists

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Major Paper presented to the
Department of Economics of the University of Ottawa
in partial fulfillment of the requirements of the M.A. Degree

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ECO 7997

Ottawa, Ontario
April 2011

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Abstract

This paper is an attempt to investigate the relationship between virtual economies and real world economies. Its main assertion is that virtual economies may be useful for studying real world economic phenomena because they could be effective tools for testing economic theories.

To support this assertion, this paper argues that virtual economies are ideal "locations" for controlled experimentation for three reasons. First, high quality data are available at low costs. Second, data gathered from realistic, complex scenarios are in the form of revealed, rather than stated, preferences. Third, there is a lack of severe real world consequences associated with market failure or unexpected outcomes in virtual economies.

These benefits are only useful if the results gleaned from the study of virtual economies are meaningful for and transferable to the study and understanding of real world economies. Thus, this research explores supply and demand characteristics using a simultaneous equations model in a specific, large scale, virtual economy: The Kingdom of Loathing. For the good examined, it is determined that the Law of Demand holds in the Kingdom. Supply of the item, on the other hand, appears to be relatively inelastic.

Though this paper uses a natural experiment rather than a controlled experiment, its findings contribute to the idea that virtual economies may be effective tools for testing economic theories.

Introduction

Technological advances tend to have important effects on the societies in which they are developed; transportation and communication advances in particular. In their time, the steam engine, the Model T Ford, and the telephone all had the effect of “shrinking” the world. Such advances facilitated the exchange of merchandise, of ideas, of culture. Economies grew and merged thanks to these developments. The total effect of the Internet on modern society is likely yet to be fully realized, and even once it has been realized, it is unlikely that measuring this effect will be possible. One important result of widespread Internet use is the development of online communities. Millions of people use the Internet to communicate and to congregate virtually. Within these virtual communities, virtual economies have developed.

This research contends that virtual economies may be useful as research tools to study real world economic phenomena. In other words, virtual economies may be an acceptable means through which to study real economic theory. There are three main reasons why this is the case. First, the availability and quality of data in virtual economies far surpass those of data in real economies. Second, data gathered from virtual economies are in the form of revealed preferences, similar to data gathered from a real world natural experiment, rather than the form of stated preferences, which is a common occurrence when researchers want more control than a natural experiment will allow. Third, virtual economies share similar day to day functionality with real world economies, such as the trading of goods and services, but real world consequences are much less severe when a virtual, rather than a real, economy fails. Given these three benefits of virtual economies, it follows that a virtual economy is the ideal place to carry out controlled experiments to test economic theories.

Naturally, if virtual economies are going to be considered viable tools for studying real world economic phenomena, the results garnered from virtual economies must be *meaningful* for and *transferable* to real economies. This research contributes to the goal of showing empirically that the study of virtual economies yields results that are both meaningful for and transferable to the real economy. To do so, this paper examines the characteristics of demand and supply for a virtual good in a particular virtual economy: *The Kingdom of Loathing*.

The results of this research are not a resounding proof that virtual economies function in the same way as real world economies, but they are encouraging. A negative and significant relationship between price and demand is found, and the presence of new game content in the form of better quality and/or less expensive substitute goods has a significantly negative effect on both supply and demand. Not all coefficients have the expected signs; the relationship between price and supply appears to be negative, though not significantly so. This is likely due to a missing variable or fairly inelastic supply. It is important to bear in mind, however, that these findings are the result of a natural experiment. As with observing real world economies, not all theoretical predictions will be proven in every empirical attempt. It is therefore important to produce a large body of empirical evidence to determine whether or not virtual economies function in ways

similar to their real world equivalents. Once it is shown that virtual and real economies act in a similar manner, testing of real world economic theories can take place in the virtual world.

The next section defines a virtual economy and other important terms relevant to this research. The third section examines in detail the benefits of studying a virtual economy while the fourth section discusses the literature of economic analysis of virtual economies. The fifth section describes the virtual world examined in this paper: The Kingdom of Loathing. The following three sections examine supply and demand characteristics in The Kingdom; the data, the model, and the results are discussed. Finally, conclusions and suggestions for further research are discussed.

What is a Virtual Economy?

In the simplest of terms, economics is “the study of how society manages its scarce resources” (Mankiw et al., 2002; 4). These resources – whether they are natural resources or skilled labour – make their home in the real world, the physical world. Thus, the world itself has a major impact on how economies function. To properly understand a virtual economy, one must first understand the world in which a virtual economy operates: the virtual world.

In her Master’s thesis, Lehtiniemi (2008) provides three definitions of *virtual worlds*. One of these definitions includes a requirement for graphical representation of the virtual world, likely because many virtual worlds are represented in such a fashion. This research will use Bartle’s less restrictive definition (Lehtiniemi, 2008; 9):

A more classification-oriented definition (Bartle 2003, 1) describes virtual worlds as non-real spaces, implemented by a computer or a network of computers, meeting the following conditions (ibid., 3-4): First, there is a set of underlying, automated rules that dictate what its participants are able to do in it. These rules correspond to the physical rules of the real world. Second, there is a distinct entity that represents a user and with which he strongly identifies. This entity is called the user’s *character* or *avatar*. Interactions between the users, and between a user and the world, take place via the characters. Third, the interaction with and in the world takes place in real time. The user’s actions in the world receive (sufficiently) immediate response. Fourth, the world is shared, which means that there are multiple users in it, and that the users may interact with each other in the world. Fifth and finally, the world is persistent. When a user goes away the world does not, and events in the world, driven by other users, occur irrespective of any single user’s presence. A persistent world exists independent of any single user.¹

¹ If the distinction between what is and what is not a virtual world is still confusing, Lehtiniemi (2008; 9) provides some concrete examples: “A web-based chat room is not a virtual world due to lacking physics; a tabletop role-playing game is not a virtual world due to lacking automation of rules, and an online strategy game is not a virtual world due to lacking characters. (Bartle 2003, 4.)”

One example of a virtual world is Second Life², “a free 3D virtual world imagined and created by its Residents” (Linden Research, Inc., 2009). Another example of a type of virtual world is the Massively Multiplayer Online Role Playing Game, or MMORPG. In such games, “players within a shared virtual environment control alternate personas, characters who retain their abilities and possessions from session to session and who can acquire additional skills or objects over time” (Burke 2002; 1-2). Graphical representation of virtual environments is common, but not necessary. MMORPGs have grown quickly in popularity over the last five years. The most popular is World of Warcraft.³ With more than 11.5 million monthly subscribers, it is the most played MMORPG in the world (Blizzard Entertainment, 2008).

Defining a virtual economy follows easily from Lehtiniemi’s definition. According to Mankiw et al. (2002; 4), an economy is simply “a group of people interacting with one another as they go about their lives.” Thus, a *virtual economy* is a group of *distinct entities*, as defined by Lehtiniemi (2008), interacting within a virtual world. In other words, a virtual economy can be “defined by the acquisition and circulation of virtual commodities and virtual services, the production and control of virtual forms of value” (Burke 2002; 2). Note that online auction sites such as E-Bay⁴ are generally not examples of virtual economies, as they facilitate the exchange of real goods – such as furniture, books, and computers – rather than that of virtual goods, which are intangible and not transferable to the real world, though some real world value can be attached to them.⁵

Benefits of Studying a Virtual Economy

As mentioned in the introduction, virtual economies are ideal “locations” for controlled experimentation for three reasons. The first is the availability and quality of data, the second is that data are in the form of revealed preferences, and the third is the lack of real world consequences resulting from changes in a virtual economy. Prior to detailing the mechanics of these benefits, a discussion on the importance of controlled experimentation is provided.

Due to the severity of real world consequences upon the occurrence of unexpected outcomes of large-scale economic experimentation, economic research has often relied upon natural or observable experiments. Such experiments are neither designed nor precipitated by economists. Rather, from time to time, the actions of various independent economic agents together create conditions where it is possible to observe the impact of a particular variable largely independent of other effects. For instance, if there are two states which are similar in most ways, but one state government decides to change its laws on workplace smoking bans, it is possible to determine the impact of the bans on the prevalence of smoking, separate from other impacts, by controlling for the variations in

² <http://www.secondlife.com/>

³ <http://www.worldofwarcraft.com>

⁴ <http://www.ebay.com/>

⁵ A small number of virtual goods are traded on E-Bay, though this is not the norm.

smoking prevalence observed in the state whose laws have not changed. Evans et al. (1999) do just this in their study “Do Workplace Bans Reduce Smoking?”

There are, however, two problems associated with relying on natural or observable experimentation. First, it is not guaranteed that the economy of interest and the control economy are exactly the same save for the difference in the variable of interest – laws enforcing workplace smoking bans, for instance. Second, natural experimentation does not allow economists to choose which economic phenomenon they would like to study; they must study the phenomenon associated with the available natural experimentation data. In this way, some portions of economic theory may be left empirically untested due to lack of data.

The RAND Health Insurance Experiment (Manning et al., 1987) is almost unique in its field as it is a randomized study on the costs of health insurance. Generally, such studies are not possible because, in order to observe the effects of a particular variable, the effects of many other variables must be controlled. Scientists have the leisure of laboratories in which to conduct and control their experiments; conditions are carefully controlled so that “all else is equal”. Economists are not so lucky. The defining characteristic of a market economy – the ability of each economic agent to choose what to produce, what to purchase, how much to save, etc. – means that randomly assigning certain incomes or products to individuals to control the effects of the variables not under investigation is almost impossible. Studies like the RAND experiment are therefore understandably rare in the real world despite their obvious benefits. In the virtual world, however, many of the downsides of controlled experimentation can be overcome.

The first benefit of studying virtual economies is that they provide incredibly high quality data very cheaply when compared to real world economies. This is the case due to the construction of virtual economies and virtual worlds. Within a virtual world, all interaction between economic agents must occur via a network of computers. A record of each interaction is therefore saved into memory, at least temporarily. It is therefore possible to collect data on every single interaction that transpires in the virtual economy. Additionally, as each interaction is recorded precisely at the time it takes place, estimation and measurement errors are negligible. Finally, as each interaction must be saved (at least temporarily) in order for it to occur, the only cost of data collection is the cost of memory storage – that is, the cost of additional hard disk drives. Data in virtual economies are therefore highly available, reliable, and low cost.

The second benefit has to do with the type of data. Data problems can be caused by data collection methods, but they can also be caused by the type of data being studied. In the absence of controlled experimentation in real economies, economists have devised alternative methods with which to study market economies. The fields of behavioural economics and experimental economics have arisen, the former generally relying on stated preferences while the latter deals with revealed preferences. In the case of stated preferences, an individual is only required to state, generally via a survey, what his or her response to a particular situation would be. For instance, a survey might ask an individual how much they would willingly give away to charity if given \$10. Their verbal or written

response is an example of a stated preference. In the case of revealed preferences, the individual voluntarily participates in an experiment, or plays a game, in which they are faced with real incentives and make decisions that have real consequences. An experimental economist would hand an individual the \$10 and then ask them to give back the amount they are willing to give away. The individual is not required to make a verbal or written response, as the returned money reveals their preference for them.

Revealed preferences are more interesting in the sense that there is no question as to the reliability of the individual's response: his or her actions speak for themselves. Can an individual who merely states that they would act a certain way be trusted to do so? According to Bertrand and Mullainathan (2001; 71), "a large experimental literature by and large supports economists' scepticism of subjective questions." On the other hand, outside of a lab environment, it is generally simpler and less costly to collect data in the form of stated preferences from the real economy. Additionally, the study of stated preferences can utilize tools such as a survey in which a complex situation is described and the respondent can be asked to give a response "all else equal". The study of revealed preferences requires a more highly controlled environment – in which all else truly is equal – in order to observe the desired effect. For this reason, experiments carried out to determine revealed preferences often simplify reality to the extreme. When studying virtual economies, researchers can enjoy the more complex situations and ease and reliability of data collection of stated preference experimental research while achieving the reliability of results of revealed preference experimental research.

One of the reasons that experiments conducted by experimental economists are on such a small scale is that experiments with real incentives are very costly to run. Another reason is that if large scale experiments fail, they have very real consequences: losses of jobs, houses, and lives can result. The third benefit of using a virtual economy is that real world consequences are lessened: individuals can lose the time they spent playing, some money if the game had a monthly fee, and the enjoyment they garnered from playing the game. Their jobs, houses, and lives are safe. As the risks involved in the virtual economy are not as high, an argument can be made that individuals will not act the same way in the virtual economy as they do in the real economy. In some ways, this is very true. For instance, characters in MMORPGs do not die permanently. There are consequences associated with dying, but they are not as severe as barring the player from the game for the rest of his or her life. In the Kingdom of Loathing, for instance, players who die in combat are considered to be "beaten up" for their next three adventures; this means that all of their combat skills or abilities are severely diminished for their next three adventures. However, the player's level and collected items remain unchanged. In this way, there are consequences to death in MMORPGs, but they are much less severe than the consequences of death in the real world.

On the other hand, many other facets of virtual worlds and virtual economies are quite similar to those of the real world and real economies. Castranova et al. (2008), for instance, show that the Law of Demand works the same way in the virtual world Arden as it does in the real world. Nash and Schneyer (2004) show that virtual economies exhibit similar supply and demand mechanics as real economies. There are certainly

some differences between real and virtual economies, but they might not be sufficiently large to discourage the use of virtual economies as economic research tools. Further research will likely cement this point of view. Note also that virtual economies present an interesting compromise for research: controlled experimentation is all but impossible in real market economies, and the results of experimental economics come from experiments that are so small scale that their application to the real economy is limited. Virtual economies are the happy median: their incentives and consequences may not be as strong as in the real economy, but they allow for large-scale experimentation at low cost.

The Introduction of Castranova et al. (2008) discusses in detail the advantages and disadvantages of natural experimentation, and makes the case for controlled experimentation. As there is a lack of real world consequences related to controlled experimentation in the virtual world and Castranova et al. (2008) shows that the technical ability to conduct such experimentation exists, the potential for meaningful results from controlled virtual world experimentation is huge, as well as exciting.

Economic Analysis of Virtual Economies

The study of economics in virtual worlds is a very recent phenomenon. There are, however, a handful of papers that show some interesting results.

One of the first papers to discuss how virtual economies can resemble real simulations is that of Burke (2002). Though no empirical work is undertaken, Burke's paper introduces an important idea that this study and many others explore more rigorously.

Nash and Schneyer (2004) explore supply and demand mechanics in the MMORGP Final Fantasy XI: Online.⁶ They examine data collected over six or seven weeks in order to study the game's economy. Their research shows that the game's economy is subject to demographic shifts, supply shocks, seasonality, and location arbitrages in the same way as a real economy. Such trends are observed graphically, but no rigorous analysis is carried out. This research studies similar data, though from a different MMORPG, and aims to take a more rigorous approach.

Chesney, Chuah and Hoffmann (2007) study virtual world experimentation. However, they do so in the experimental economics sense: their experiments in Second Life provide real incentives, but are small scale, just as such experiments are in the real world. Though the authors do not undertake large-scale experimentation (which is further discussed in the next section), their research yields some impressive results. Namely, that (small scale) experiments work just as well in the virtual world as in the real world, and that the population in virtual worlds does not appear to be subject to selection bias. One could assume, for instance, that only a certain type of person would partake in virtual world interactions, and that this would influence experimental results. However, according to Chesney et al. (2007), there is no evidence of such bias in Second Life. Due

⁶ <http://www.ffxionline.com/>

to time and resource limitations, this research does not check for selection bias in *Kingdom of Loathing*, but rather assumes that the effects of such a bias are negligible, as per the results of Chesney et al. (2007). Selection bias in virtual worlds is certainly a candidate for further research to ensure that, if it is present, any effects it may have are truly negligible in most circumstances.

Natural experimentation in large games was the subject of a study by Castranova (2005). He studied two MMORPGs and showed that natural experimentation – the likes of which is common in real world economic studies – in heavily populated virtual worlds is a valuable research tool for economists.⁷ In this sense, Castranova (2005) posits that results from natural experimentation in virtual economies are *meaningful* for and *transferable* to the real world; his research provides important empirical support for this project.

In a similar vein, Castranova et al. (2008) carry out a controlled experiment using virtual economies to test whether or not the Law of Demand, which states that the price of a good and its quantity demanded are inversely related, holds in virtual economies. Two versions of the virtual world Arden were created to be the same in every respect, with one exception: the price of healing potion in one world was twice the price of the same potion in the other world. The sample size used was quite small: each game only had 43 players (assigned randomly to each world). However, the result was clear: 43.1% fewer potions were sold in the world where they were more expensive. This result provides empirical support for the claim that findings in virtual economies are meaningful for and transferable to the real world. It also demonstrates one of the benefits of studying virtual worlds – the ability to perform controlled experimentation in virtual economies – which are discussed in the next section.

Finally, Lehtiniemi (2008) examines macroeconomic indicators in a virtual economy as a Master's thesis. As the work is a thesis, it contains a comprehensive literature review as well as key definitions. These were very useful in the completion of this project. Additionally, Lehtiniemi (2008) shows that inflation exists in virtual economies just as it does in real economies, lending credence to the assertion that virtual economies can be used as tools to study real world economic phenomena.

Virtual World Studied: The Kingdom of Loathing⁸

The Kingdom of Loathing (KoL)⁹ is a free and comical MMORPG. Created in 2003 by Zack “Jick” Johnson, KoL is operated by Asymmetric Publications and is currently in Open Beta format (Asymmetric Publications, LLC, 2008). This means that KoL is open for anyone who wants to play, but the game is not “finished” in the sense that adjustments are made continually: new items are added, new adventures are added,

⁷ The use of natural experimentation in economics is discussed further in the next section.

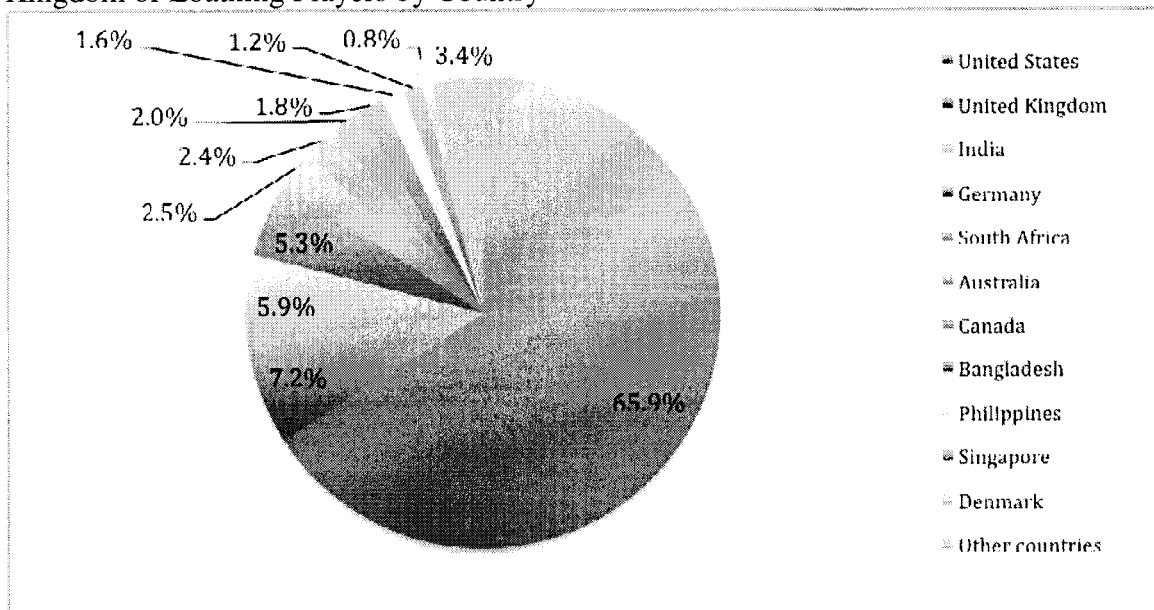
⁸ Information that is not sourced directly was gleaned from having played the game.

⁹ <http://www.kingdomofloathing.com/>

and stat point gains from adventures, food and alcohol are tweaked. KoL has about 200,000 active accounts and between 60,000 and 100,000 regular players.¹⁰

Figure 1 below shows the distribution of KoL players from each country. As the figure shows, most players are from the United States, while only 2% are from Canada (Alexa Internet, Inc., 2009).

Figure 1
Kingdom of Loathing Players by Country



Source: Alexa Internet, Inc. (2009).

The goal of the game is to defeat the Naughty Sorceress. To do so, players start at Level 1 and go on adventures in order to gain experience, advance to higher levels, and collect helpful items and Meat, the Kingdom's currency. Experience comes in the form of stat point gains. A player advances to a higher level by increasing their main experience stat, which is determined by the type of character they choose to play. There are three types of experience stats: muscle, mysticality, and moxie. Each player has points in all three stat categories, though increasing the point total in their main stat is the only way a player can advance to higher levels. Once a player has gained enough experience and levels, he or she can then face the Naughty Sorceress, and hopefully defeat her.

Each (real life) day, players are granted forty adventures. They can adventure in a variety of locations; some places offer higher stat, item, and Meat gains, but they are also more dangerous in the sense that it is possible to lose hit points much faster and more frequently. Hit points determine how much damage a character – a player – can take. A player's muscle stat determines the number of hit points that player has. When a player's

¹⁰ Account information gleaned from an email exchange with Kevin Simmons, an employee of Asymmetric Publications.

hit point count reaches zero, they must rest (which uses up adventures) or use a Healing Potion to regain some hit points before they can adventure once more.

Players can increase their number of daily adventures by eating and drinking, though their stomachs and livers can only take so much. Fullness and Drunkenness are two stats separate from a player's experience. Each type of food has a certain Fullness value attached to it, and each type of alcohol is associated with a certain amount of Drunkenness. This means that each time a player "eats", he or she becomes increasingly "full", and the more a player "drinks", the more "drunk" he or she becomes. Eventually, the player is too "full" to eat any more. Interestingly, a player can always consume more alcohol, though at a certain point his or her level of Drunkenness takes a toll; the player's main stats will decrease to such an extent that adventuring becomes a very risky endeavour.

Fullness and (safe) Drunkenness are capped at certain amounts to limit the number of adventures a player can take each (real life) day. At the beginning of the game, with no modifiers,¹¹ a player's Fullness and (safe) Drunkenness are each limited to 15 points. This means that players need to pay close attention to the types of food and drink they consume in order to maximize the number of adventures they can take each day. There is therefore a clear trade-off between Fullness and (safe) Drunkenness points and the number of adventures: the more adventures a player can get for each Fullness or Drunkenness point consumed, the better. Naturally, foods with higher Adventure/Fullness ratios are more desirable. They are also more costly when purchased, and are more dangerous to acquire from adventuring.

In addition to acquiring items by adventuring, players can purchase items from Non-Player Characters (NPCs) – which are controlled by the game rather than other players – as well as from other players. At Level 9 and above, players are permitted to open shops in the Mall of Loathing. Sellers can choose the quantities they wish to sell and can set their own prices, though each item has a minimum price at which it is allowed to be sold. At Level 5 and above, players are allowed enter the Mall to purchase items. Certain items are not tradable due to game rules, but most items are.

As KoL is free to play, funds for the servers and game designers/operators are raised by selling game merchandise and by "donations". For each US\$10 "donation" to KoL, a player receives a special item called a Mr. Accessory; in effect, the "donation" is a purchase of a virtual good rather than some form of charity. These items are tradable, and generally go for more than 4,000,000 Meat in the Mall. Interestingly, intrepid KoL players can mail in a CND\$10 bill to purchase a Mr. Eh – a pun on the commonly used term for a Mr. Accessory: Mr. A. The stat point gains from a Mr. Eh are proportional to the stat point gains from a Mr. A and change according to fluctuations in the Canadian-American exchange rate. There are two caveats: first, stat point gains from a Mr. Eh never exceed those from a Mr. A, even when the Canadian Dollar trades for more than the American Dollar. Second, unlike Mr. Accessories, Mr. Ehs are not tradable.

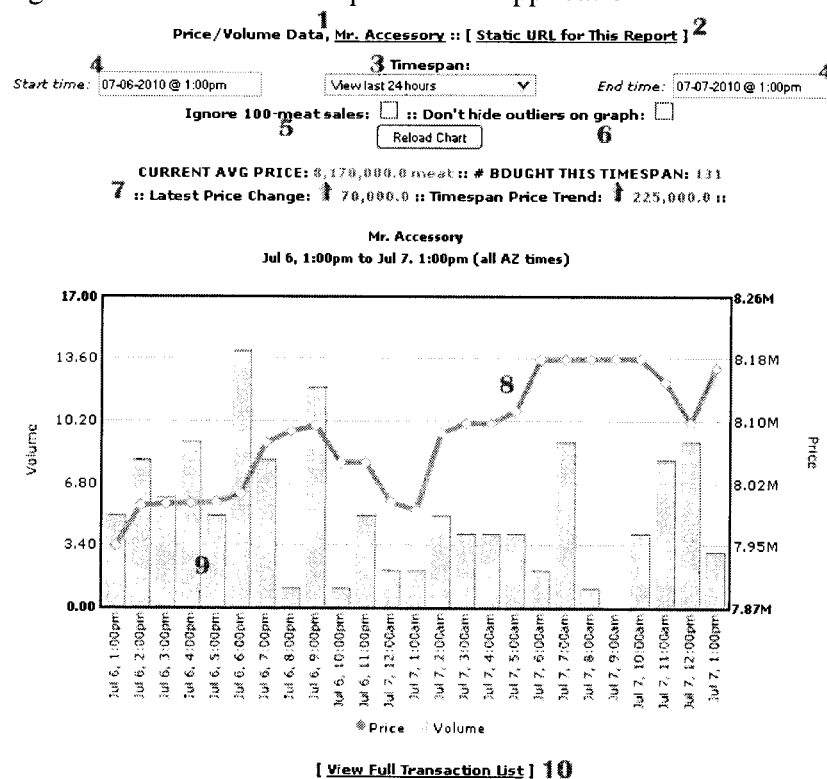
¹¹ Certain items can increase a player's maximum Fullness or (safe) Drunkenness.

Data

In theory, any kind of data can be gathered from an MMORPG because all interactions occur online, and some record of the interaction is made, somewhere, on some server, if only temporarily. This means that precise data are potentially collectable, whether they be a player's total assets, his level of consumption, his savings rate, his income, his level, the number of adventures he undertakes...

For the purpose of this research, no effort was made to acquire absolutely all information. Rather, only information that is readily available is used. Such data are goods market equilibrium price and quantity data from the Kingdom of Loathing's Mall.

Figure 2
The Reporting Function of the Marketplace v2.0 Application



Source: KoL Marketplace v2.0 Help and Credits (2010).

The price and quantity data for this project were collected from the Kingdom of Loathing Marketplace v2.0 application.¹² The Marketplace application provides market data for each tradable item in the game. Three functions allow access to these data.¹³ A search/browse function allows the user to choose the item whose market data they would like to see. A reporting function displays the data in a graph, allows for a certain degree of customization of the data, and provides a means to export the data. Finally, a 'market

¹² <http://kol.coldfront.net/index.php/content/view/1903/146/>

¹³ KoL Marketplace v2.0: Help and Credits: <http://kol.coldfront.net/newmarket/help.php>.

ticker' function shows price changes within the last 30 minutes. Figure 2 shows the reporting function of the application.

The reporting function provides:¹⁴

- The name of the item whose data is being shown (1),
- A link to the static URL for the specific data reported (2),
- The ability to choose the time span of the data through either a drop-down menu (3) or manual setting (4),
- The ability to ignore 100-Meat sales, which can be outliers (5),
- The ability to show or hide outliers (6),
- Some relevant data aggregation (7),
- The price trend (8),
- The quantity sold trend (9), and
- A link to the full transaction list (10).

These data are publicly available. In this way, it is both easy to reproduce the results of this research and easy to ensure that the data are reliable. This research uses Marketplace data for the period from 1 August 2010 to 24 March 2011. The median daily price and the daily quantity sold are used.

In addition to the Marketplace data, some key data were collected from the Old Announcements pages on the official Kingdom of Loathing website,¹⁵ the Kingdom of Loathing Forums,¹⁶ and a website called the KoL Wiki.¹⁷ As mentioned in the section describing the Kingdom of Loathing, the game is in Open Beta format, meaning the content is updated rather frequently and without notice. The Old Announcements pages on the KoL website keep track of all the game update announcements the game's creators have made dating back to 31 January 2003. Thus, when the game is updated the changes are tracked and described, facilitating the analysis of a natural experiment.

As a general rule, online forums are not necessarily reliable sources of information. However, the game's designers often use the forums to post about technical changes to the game. These posts elaborate on the announcements made on the official site, providing key information on how the game, and therefore the economy, has changed.

The KoL Wiki is dedicated to providing information about the Kingdom, and, as its name suggests, it is a wiki. The Higher Education Academy's Economics Network¹⁸ defines a wiki as "a website that visitors can edit using their browser. Groups can use a wiki to author documents collaboratively" (University of Bristol, 2008). The most

¹⁴ KoL Marketplace v2.0: Help and Credits: <http://kol.coldfront.net/newmarket/help.php>.

¹⁵ <http://www5.kingdomofloathing.com/static.php?id=oldannouncements> and <http://www5.kingdomofloathing.com/static.php?id=oldannouncements2010>

¹⁶ <http://forums.kingdomofloathing.com/vb/showthread.php?t=183720>

¹⁷ http://kol.coldfront.net/thekolwiki/index.php/Main_Page

¹⁸ <http://www.economicsnetwork.ac.uk/>

popular example of a wiki is the Wikipedia, an online encyclopaedia.¹⁹ Though wikis are generally frowned upon for use in academic work as they are not considered to be an authoritative source, the nature of the KoL Wiki is such that it is very useful for this research. For online gaming communities, such as the KoL community, wikis are very useful for sharing information; with many people contributing to data collection, relevant data are collected more quickly and are reviewed for accuracy by an interested group rather than an individual. Additionally, as KoL is in Open Beta format, the game is always changing, and updates to game information are needed frequently. In this way, the community is the authoritative source for KoL information. For these reasons, the KoL Wiki is deemed to be an appropriate source for this research. It provides detailed game mechanics information, including Adventure/Fullness ratios.

One of the main benefits of working with virtual economies is that data limitations are minimized as compared to those faced in real economies. There can be errors in data collection if the programmes are buggy, but sufficient code review and allowing code to be publicly available should keep such errors to a minimum. However, errors resulting from problems such as measurement error are not important because such things do not exist in the virtual world. For instance, if a virtual truck is said to weigh 3500 kg, it weighs precisely that amount.

With respect to choosing the good or goods to be examined, there are four issues to consider. First, the good is expected to be normal in the sense that quantity demanded will increase as the price falls, all else equal. Second, the good must be selling above the pre-determined price floor. In this way the observed price and quantity reflect the true market determinants rather than the result of a market intervention. Third, the good must sell a large number of units in order to minimize 'missing' data (days on which nothing is sold) as well as outliers. Fourth, the good must be affected by the chosen game update.

Over the time period under consideration, one major game update occurred and four minor game updates occurred. The four minor game updates occurred in July and August; it would be difficult to analyze the changes due to these updates as there are insufficient data points prior to their occurrence. Additionally, as the changes are minor, the technical details of these changes are discussed only superficially. Deducing expected outcomes from these changes given limited information would be difficult. The major game update, on the other hand, occurs on 8 September 2010 and is discussed at length. Thus, the Cooking Changes game update is used.

Prior to the Cooking Changes update, 'cooking' involved combining two ingredients, themselves generally food items, to create a different food item. Each time two ingredients were combined in this manner, the player lost one adventure. For food items that required the combination of many ingredients, an adventure was lost at each step. According to game designer Jick's forum post, the Cooking Changes update removed the adventure cost for all ingredients except those classified as 'fancy', though purchasing an item called a Chef-in-a-Box would remove the adventure cost for these

¹⁹ <http://www.wikipedia.org/>

ingredients as well.²⁰ In effect, this change increases the number of adventures a player can take each day, effectively increasing his income. A slew of other changes were implemented as well. For instance, food items are now categorized by quality in terms of Adventure/Fullness ratio, and these qualities are displayed in the item descriptions, improving a player's ease of access to information. Also, it is now possible to search the Mall by food quality, further improving information access and therefore competition, perhaps leading to increased arbitrage between substitute goods. As food items were being labelled according to their quality, the game designers determined that five food items were outliers in terms of their quality. In response to this discovery, the average yield of adventures and the range of adventures gained from the five types of key lime pies were reduced.

Boris's key lime pie, one of the five key lime pies, is clearly affected by the Cooking Changes game update. It also satisfies the other three requirements outlined previously for choosing a good for examination. Thus, this paper examines the supply and demand characteristics of Boris's key lime pie.

There are two limitations associated with the data used for this project. First, for two of the substitute goods and one of the inputs considered, there are days on which the items did not sell. For these days, both price and quantity are left blank. Second, only Mall data are examined, but the Kingdom's economy extends beyond the Mall. For instance, certain items aren't tradable, player to player trades via kmail – KoL email – are not recorded, and items purchased from Non-Player Characters (NPCs) aren't tracked. It is the author's belief that these limitations are sufficiently benign so as to not significantly impact the results of this study, though there is certainly room for future improvements.

Model

Two of the most fundamental relationships in real world economies are those of supply and demand. This research aims to examine the supply and demand characteristics of a particular good in the KoL economy: Boris's key lime pie.

An econometric model of a goods market equilibrium is as follows (Greene, 2008; 354):

$$\begin{array}{ll} \text{Demand equation:} & q_{d,t} = \alpha_0 + \alpha_1 p_t + \alpha_2 x_t + \dots + \epsilon_{d,t}, \\ \text{Supply equation:} & q_{s,t} = \beta_0 + \beta_1 p_t + \dots + \epsilon_{s,t}, \\ \text{Equilibrium condition:} & q_{d,t} = q_{s,t} = q_t. \end{array}$$

As the above model is one of simultaneous equations, a problem of identification arises: are the parameters of interest estimable? Prior to addressing this issue, the determinants of supply and demand are outlined.

²⁰ <http://forums.kingdomofloathing.com/vb/showthread.php?t=183720>

Quantity demanded is determined by its own price, income, prices of related goods (complements and substitutes), tastes or preferences, and expectations (Mankiw et al., 2002). For the quantity demanded variable, the logarithm of the daily volume sold of Boris's key lime pie is used. The logarithm of the median daily price in Meat of Boris's key lime pie is used for the price variable. Data for both of these variables are taken from the Marketplace application and then transformed using the log function.

Unfortunately, none of the available data directly provide information on income. However, an approximation of Gross Domestic Product (GDP) could be calculated by multiplying the daily median²¹ price of each item by its daily volume sold to produce the daily value sold for each item. These values could then be summed to produce daily GDP, and the logarithm would be taken to produce the income variable. Two problems would arise from using such a calculation as a variable for income. First, there may be important variation from day to day. Variation could arise from the sale of a rare, expensive item, which could substantially increase GDP for one day without a corresponding increase in income. In other words, this calculation of GDP might not be a good approximation of the income variable. A second problem is that the calculation produces nominal, rather than real, GDP. Lehtiniemi (2008) shows that virtual economies are subject to inflation just as real economies are.

In addition to these two problems, there are two technical issues. First, the servers used to store the Marketplace data have limited capacity due to real world budget constraints. The individuals who maintain the servers have therefore requested that users be judicious in their data downloads in order to prevent a server overload. Downloading price and quantity data for every item in the KoL economy since 1 August 2010 would almost certainly result in a server overload. Second, even if server overloads were not an issue, each item's data would need to be formatted individually. As there are thousands of items in the KoL economy, such an undertaking would be infeasible for this research. Thus, despite important drawbacks, no income variable is included.

There are two types of related goods: substitutes and complements. In order to determine the effect of the prices of these related goods on demand, one must first determine which goods are related to Boris's key lime pie. A substitute good is one that is very close in function and in quality to the original good. As consuming food in the Kingdom allows a player to increase his or her daily adventures, a substitute good would be one that provides a similar number of adventures per Fullness point. Food also gives players stats; the number and type of stat points gained from eating each type of food should also be considered. If a food both has the same Adventure/Fullness ratio and gives the same amount of the same type of stat as another, then they are effectively perfect substitutes. The KoL Wiki provides detailed information on each food's Adventure/Fullness ratio, as well as the stat point gains for each type of food.

Recall that food is categorized by its quality in terms of Adventure/Fullness ratio. Food that gives between 3 and five adventures for each point of Fullness falls in the

²¹ Generally, the average price is used to calculate GDP. Here, the median price would be used as a proxy for the average price as the average price is not available.

Awesome category (“Category: Food”, 2011). There are 96 food items in this category, including Boris’s key lime pie. Trading is not allowed for ten of these items. Consequently, there is no price associated with these items, meaning they are not useful as substitute goods. Eleven of these items are obtained from one-time past events or aspects of the game that are obsolete. The number of these items in existence in the game is constant at best and is likely decreasing; the scarcity of these items means that they are not useful as substitute goods. The remaining food items can be divided into four categories according to stat point gain. As Boris’s key lime pie provides an increase to the muscle stat, food items which provide an increase to this stat could be used as substitute goods. There are 11 such food items. Some foods also have a minimum level requirement in order for a player to consume them. Taking into account the Adventure/Fullness ratio, the stat point gain, and the level requirement, six food items are used as substitute goods for Boris’s key lime pie. Table 1 shows the stat point gains for each of these food items.

Table 1
Adventure/Fullness Ratio, Stat Point Gains, and Level Requirements for Boris’s Key Lime Pie and its Substitute Goods

Type of Food	Adventure/Fullness Ratio	Stat Points Gained	Level Requirement
Boris’s Key Lime Pie	3.75	28-33 Muscle	6
Tofurkey Gravy	3.25	70-75 Muscle	5
Tofurkey Leg	3.5	70-75 Muscle	5
Knoll Lo Mein	4.375	30-34 Muscle	6
Spaghetti with Skullheads	4.0833	47-52 Muscle	6
Crimbo Pie	3.6667	24-45 Muscle	7
Knob Sausage Chow Mein	4.9	72-76 Muscle	7

Source: The KoL Wiki (2011).

An increase in the price of a complementary good increases the demand for the good under consideration. However, Fullness is, for the most part, a fixed stat in the Kingdom: once a player is “full”, he or she cannot “eat” any more. There is one exception: a spice melange is an item that can be used once each day. It reduces a player’s Fullness and (safe) Drunkenness by three points each. Thus, using a spice melange, a player can increase the amount of food they consume, thereby increasing their demand for food. This research considers the spice melange to be a complementary good for all foods, and Boris’s key lime pie in particular.

There are four more goods related to Boris’s key lime pie; they are the remaining key lime pies. Just as Boris’s key lime pie have an Adventure/Fullness ratio of 3.75 and a muscle stat point gain of 28-33, Jarlsberg’s key lime pie and Sneaky Pete’s key lime pie provide the same Adventure/Fullness ratio and equivalent stat point gains, though for different stats. Jarlsberg’s is associated with mysticality while Sneaky Pete’s is associated with moxie. All three of these key lime pies also provide the player with a distinct key when the pie is consumed. This key is required to complete one of the game’s primary quests. The remaining two key lime pies provide the same Adventure/Fullness ratios and smaller stat point gains, though stat points are gained in all three stats. A key difference, however, is that these two key lime pies provide the means through which to build keys

rather than the keys themselves. Thus, a player will need to consume multiple digital key lime pies and star key lime pies in order to build the digital and star keys. It is clear that the key lime pies are related goods: but are they complements or substitute? A player must consume all of the pies in order to complete the quest, so in that sense the pies are complements. But the pies can also be consumed in order to gain adventures, making them substitutes as well.

Tastes or preferences are assumed to be constant for two reasons. First, “While economic theory posits the importance of tastes, most econometric specifications posit constant preferences or tastes, leaving price and income effects as sole determinants of demand” (Baltagi and Griffin, 2006; 168). By assuming constant preferences, the difficulty in ascertaining consumer preferences is removed. The second, and more convincing, reason for assuming constant preferences is as follows. In the Kingdom of Loathing, each good in the Mall has a clearly defined value, a value that is the same for each player. For instance, when eaten, a goat cheese pizza will give the player 3-10 more adventures, increase their moxie stat by 15-18 points, and count for 3 Fullness points (“Goat cheese,” 2009). Recall that a player can only eat so much every day – a player’s maximum Fullness without modifiers is 15 (“Fullness,” 2008). Certain foods have a much higher Adventure/Fullness ratio, but they cost more as well. Thus, a player will prefer the foods with the highest Adventure/Fullness ratios for the least amount of Meat.

In this sense, each player (at a given level) will have the same preferences. And these preferences will be unlikely to change unless the stat points given by particular items change, or new items are introduced. During the time when data for this project were collected, the only major change to KoL items was the Cooking Change (“Old Announcements for 2010,” 2011 and “Old Announcements for 2011,” 2011). Thus, the assumption for this project that preferences remained constant appears to be valid.

Finally, as no major game changes are announced prior to their implementation, player expectations are assumed to be constant between game updates.

Three additional variables are added to the demand equation. A dummy variable for the game update is included, taking the value of 0 before the game update and the value of 1 as of 8 September 2010, when the Cooking Changes were implemented and announced. A weekend dummy variable is also included, taking on the value of 1 for Fridays, Saturdays, and Sundays, and the value of 0 for the remaining days of the week. This variable controls for shifts in game activity throughout the week. As game play consumes one’s leisure time, it is reasonable to assume that more activity takes place in the KoL economy over the weekend than during the week, when leisure time is limited by real world employment. A final dummy variable indicates the presence of the Crimbo season. During the weeks leading up to and immediately following Christmas, additional content in the form of items and adventures is added to the Kingdom in order to celebrate the Kingdom’s version of Christmas: Crimbo. The presence of these new items and adventures is likely to change market behaviour; the Crimbo dummy variable takes on the value of 1 during Crimbo and 0 the rest of the year. Note that Crimbo Pie is not exclusively available during Crimbo, and thus is suitable as a substitute good. Table 2

summarizes the variables used in the model's demand equation. Note that with the exception of the dummy variables, all variables have been transformed using the log function. Additionally, the logarithms of the prices of related goods are lagged. These variables are lagged in order to prevent any endogeneity problems, as prices and quantities for all goods are simultaneously determined in the goods market.

Table 2
Variable Names and Descriptions for the Model's Demand Equation

Variable Name	Variable Description
qlog_bklp	Logarithm of the daily volume sold of Boris's key lime pie
plog_bklp	Logarithm of the median daily price of Boris's key lime pie
plaglog_sm	Logarithm of the lagged median daily price of spice melange
plaglog_tg	Logarithm of the lagged median daily price of tofurkey gravy
plaglog_tl	Logarithm of the lagged median daily price of tofurkey legs
plaglog_klm	Logarithm of the lagged median daily price of knoll lo mein
plaglog_sws	Logarithm of the lagged median daily price of spaghetti with skullheads
plaglog_cp	Logarithm of the lagged median daily price of crimbo pie
plaglog_kscm	Logarithm of the lagged median daily price of knob sausage chow mein
u	Dummy variable: 1 if Cooking Changes implemented, 0 else
c	Dummy variable: 1 if Crimbo Season, 0 else
w	Dummy variable: 1 if Friday, Saturday, or Sunday, 0 else

Quantity supplied is determined by its own price, input prices, technology, and expectations (Mankiw et al., 2002). As with the quantity demanded variable, the logarithm of the daily volume sold of Boris's key lime pie is used for the quantity supplied variable. The logarithm of the median daily price in Meat of Boris's key lime pie is used for the price variable. Data for both of these variables are taken from the Marketplace application. Boris's key lime pie can be created by cooking Boris's key lime and a pie crust, and so the prices of each of these items are used as input prices. The variables used in the supply equation are the lagged logarithms of these input prices. This is done to prevent endogeneity issues, as with the demand equation of the model. The Cooking Changes game update changes the technology used for cooking, as combining ingredients can now be done more cheaply. The game update dummy variable should capture this effect. Finally, similar to the assumptions used for the model's demand equation, player expectations are assumed to be constant except as a result of the Cooking Changes game update. Table 3 summarizes the variables used in the model's supply equation, including the additional dummy variables.

Table 3
Variable Names and Descriptions for the Model's Supply Equation

Variable Name	Variable Description
qlog_bklp	Logarithm of the daily volume sold of Boris's key lime pie
plog_bklp	Logarithm of the median daily price of Boris's key lime pie
plaglog_bkl	Logarithm of the lagged median daily price of Boris's key lime
plaglog_pc	Logarithm of the lagged median daily price of pie crust
GU	Dummy variable: 1 if Cooking Changes implemented, 0 else
C	Dummy variable: 1 if Crimbo Season, 0 else
W	Dummy variable: 1 if Friday, Saturday, or Sunday, 0 else

Having considered the determinants of supply and demand for Boris's key lime pie, attention is now given to the problem of identification.

This project's structural market equilibrium model is as follows. Note that the P_comp_{t-1} , P_sub_{t-1} , and P_input_{t-1} variables are vectors as they represent the lagged logarithms of the prices of all complements, substitutes, and inputs, respectively.

Demand Equation:

$$Q_{d,t} = \alpha_0 + \alpha_1 P_t + \alpha_2 P_comp_{t-1} + \alpha_3 P_sub_{t-1} + \alpha_5 U_t + \alpha_6 C_t + \alpha_7 W_t + \varepsilon_{d,t}$$

Supply Equation:

$$Q_{s,t} = \beta_0 + \beta_1 P_t + \beta_4 P_input_{t-1} + \beta_5 U_t + \beta_6 C_t + \beta_7 W_t + \varepsilon_{s,t}$$

Equilibrium Condition:

$$Q_{d,t} = Q_{s,t} = Q_t$$

Where:

- $Q_{d,t}$ is the log of the quantity demanded of Boris's key lime pie,
- P_t is the log of the price of Boris's key lime pie,
- P_comp_{t-1} are the logs of the lagged prices of the complements,
- P_sub_{t-1} are the logs of the lagged prices of the substitutes,
- U_t is the game update dummy variable,
- C_t is the Crimbo seasons dummy variable,
- W_t is the weekend dummy variable,
- $Q_{s,t}$ is the log of the quantity supplied of Boris's key lime pie,
- P_input_{t-1} are the logs of the lagged prices of the inputs,
- Q_t is the log of the equilibrium quantity of Boris's key lime pie.

Solving these equations for the logs of the price and the quantity of Boris's key lime pie, the reduced form of the model is as follows.

$$(1) \quad P_t = (\alpha_0 - \beta_0)/(\beta_1 - \alpha_1) + \alpha_2 P_comp_{t-1}/(\beta_1 - \alpha_1) + \alpha_3 P_sub_{t-1}/(\beta_1 - \alpha_1) \\ + (\alpha_4 - \beta_4)P_input_{t-1}/(\beta_1 - \alpha_1) + (\alpha_5 - \beta_5)U_t/(\beta_1 - \alpha_1) \\ + (\alpha_6 - \beta_6)C_t/(\beta_1 - \alpha_1) + (\alpha_7 - \beta_7)W_t/(\beta_1 - \alpha_1) + (\varepsilon_{d,t} - \varepsilon_{s,t})/(\beta_1 - \alpha_1)$$

$$(2) \quad Q_t = \beta_0 + (\alpha_0\beta_1 - \beta_0\beta_1)/(\beta_1 - \alpha_1) + (\alpha_2\beta_1 P_comp_{t-1})/(\beta_1 - \alpha_1) \\ + (\alpha_3\beta_1 P_sub_{t-1})/(\beta_1 - \alpha_1) - (\alpha_1\beta_4 P_input_{t-1})/(\beta_1 - \alpha_1) \\ + (\alpha_5\beta_1 U_{t-1} - \alpha_1\beta_5 U_{t-1})/(\beta_1 - \alpha_1) + (\alpha_6\beta_1 C_{t-1} - \alpha_1\beta_6 C_{t-1})/(\beta_1 - \alpha_1) \\ + (\alpha_7\beta_1 W_{t-1} - \alpha_1\beta_7 W_{t-1})/(\beta_1 - \alpha_1) + (\beta_1\varepsilon_{d,t} - \alpha_1\varepsilon_{s,t})/(\beta_1 - \alpha_1)$$

In the reduced form of the model, the endogenous log(price) variable, P_t , is no longer on the right hand side. As the logarithms of the prices used for the complements,

substitutes, and inputs are lagged so as not to be endogenous, the reduced form coefficients and covariance matrices can be consistently estimated by OLS (Greene, 2008). The problem, however, is that the reduced form coefficients are not the coefficients of interest, but rather it is the structural model's coefficients that are of interest. This is the issue that is referred to as the problem of identification: given the information gleaned from the reduced model, is it possible to determine the structural coefficients?

Identification is not always possible. However, Greene (2008) suggests that, with sufficient additional information, such as theoretical restrictions, identification becomes possible. In the case of the structural model presented above, the lagged log(prices) of the complementary and substitute goods only appear in the demand equation while the lagged log(prices) of input goods only appear in the supply equation. These are effectively theoretical restrictions excluding some variables from each of the structural equations. These exclusions allow for each of the structural parameters to be uniquely solved. In other words, they allow for identification. This is in line with Greene's (2008; 369) rule of thumb for identification: "If every equation has its own predetermined variable, the entire model is identified."

Having established that identification is possible for this model, attention is turned to estimation. Three main methods exist for estimating this type of model: indirect least squares estimation, limited information direct estimation, and full information direct information (Greene, 2008). The most straightforward approach is that of indirect estimation using two stage least squares, and that is the method used here. The reduced form equation for the log of the price is used in the first stage to obtain estimates for this variable, and these estimates are plugged into the structural equations in the second step. In this way, consistent estimators are obtained for the structural coefficients and the correct standard errors are obtained as well.

The expected results for the demand equation are as follows. Demand for normal goods decreases as their price increases, so α_1 should be negative. Demand for normal goods decreases as the prices of its complement goods increase, so α_2 should be negative. Demand for normal goods increases as the prices of its substitute goods increase, so α_3 should be positive. The expected demand response to the Cooking Changes game update is ambiguous, as demand for Boris's key lime pie would likely fall in response to change in quality of the key lime pies, but the increased income due to the effective increase in adventures may increase demand. Thus, there is no expectation placed on the sign or the magnitude of α_5 . The demand response to the Crimbo season is difficult to predict, as many new items and adventures are available during this time and their combined effect is unknown. However, α_6 may be negative as the new, though temporary, Crimbo game content is likely more interesting or valuable than the standard game content. Finally, players have more leisure time on weekends than on weekdays with which to adventure in the Kingdom, so α_7 is likely positive.

The expected results for the supply equation are as follows. Supply of normal goods should increase with an increase in price, so β_1 should be positive. Supply of

normal goods should decrease with an increase in input prices, so β_4 should be negative. The reduction in cooking costs due to the Cooking Changes game update should result in a higher quantity supplied, so β_5 should be positive. The supply response to the Crimbo season is, as previously mentioned, difficult to predict. It is likely that Crimbo game content will have a negligible effect on supply, though quantity sold may drop due to demand effects. Thus, β_6 may be equal to 0. Finally, similar to the demand response, supply is likely to increase as the number of players adventuring increases, so β_7 is likely to be positive.

Results

Table 4 shows the descriptive statistics for each variable included in the model. The lagged variables have a maximum of 266 observations while the remaining variables have a maximum of 267 variables. However, the logarithms of the price variables for the tofurkey gravy, the tofurkey leg, and Boris's key lime are missing some observations as there were days when these items were not sold. In order to ensure comparability across regressions, observations with incomplete data are excluded from the model. Thus, the model is restricted to using 246 observations, as seen in the table. The three dummy variables have the expected maximums and minimums of 1 and 0, respectively.

Table 4
Descriptive Statistics for Model's Variables

Variable Name	N	Mean	Standard Deviation	Minimum	Maximum
qlog_bklp	246	3.546152	0.431857	2.079442	5.327876
plog_bklp	246	8.292659	0.290157	5.505332	8.846497
w	246	0.426829	0.495626	0	1
c	246	0.162602	0.369754	0	1
u	246	0.772358	0.420165	0	1
plaglog_jklp	246	8.315945	0.356762	5.505332	8.922658
plaglog_spklp	246	7.99055	0.26002	5.505332	8.318645
plaglog_dklp	246	8.258509	0.353192	5.505332	8.662159
plaglog_sklp	246	7.423029	0.476627	5.505332	8.449771
plaglog_sm	246	12.85229	0.567011	4.60517	13.59237
plaglog_tg	246	6.561557	0.514837	2.70805	7.600903
plaglog_tl	246	6.454861	0.509455	4.60517	7.313221
plaglog_klm	246	7.267086	0.228493	5.31812	7.919356
plaglog_sws	246	8.071954	0.413708	4.804021	8.731659
plaglog_cp	246	5.936956	0.260283	5.075174	6.246881
plaglog_kscm	246	8.43357	0.228341	4.969813	8.679004
plaglog_bkl	246	8.260108	0.240228	7.376508	8.824677
plaglog_pc	246	4.843333	0.347879	4.60517	6.907755

Table 5 provides descriptions for the nine cases considered for the demand equation. Each case is a different specification for the demand equation. The purpose of considering a variety of cases is to see if the own price effect, as well as other effects, are consistent across specifications. Case 1 includes all of the complements and substitutes, including the key lime pies. The remaining cases exclude groups of these items. For instance, some cases include only two of the key lime pies, some cases exclude all key lime pies, and some cases include only the best substitutes.

Table 5
Demand Equation Cases

Case	Description
1	All complements, substitutes, key lime pies, and inputs are included in the model.
2	All complements, key lime pies, and inputs are included in the model. Only the best substitutes are included*.
3	All complements, substitutes, and inputs are included in the model. Only Jarlsberg's key lime pie and Sneaky Pete's key lime pie are included.
4	All complements and inputs are included in the model. Only the best substitutes are included*.
5	Only Jarlsberg's key lime pie and Sneaky Pete's key lime pie are included.
6	All complements, substitutes, and inputs are included in the model. Only the digital key lime pie and the star key lime pie are included.
7	All complements and inputs are included in the model. Only the best substitutes are included*.
8	Only the digital key lime pie and the star key lime pie are included.
9	All complements, substitutes, and inputs are included in the model. No key lime pies are included in the model.
	All complements and inputs are included in the model. Only the best substitutes are included*.
	No key lime pies are included in the model.
	All inputs and key lime pies are included in the model. No complements or substitutes are included.

The best substitute good for each minimum level requirement is chosen. These goods are: the tofurkey leg, the knoll lo mein, and the Crimbo pie.

Table 6 examines the instruments used for the demand equation. As seen in Equation (1), the reduced form equation for P_t , all variables except Q_t are included in the first stage regression. Of these variables, only two are excluded from the structural demand equation: the input price variables `plaglog_bkl` and `plaglog_pc`. As Table 6 shows, these two variables appear to be significant according to their p-values. However, as seen in Staiger and Stock (1997), the critical value for a first stage regression F statistic is 10. With the exception of case 7, none of the F statistic values approach this threshold. The instruments may therefore be weak despite the lack of correlation with Q_t , as show in the structural demand equation.

Table 6
Demand Equation Instruments

Case	Instruments	F Statistic	p-value
1	<code>plaglog_bkl</code> , <code>plaglog_pc</code>	F(2, 229) = 3.01	0.051
2	<code>plaglog_bkl</code> , <code>plaglog_pc</code>	F(2, 232) = 6.24	0.002
3	<code>plaglog_bkl</code> , <code>plaglog_pc</code>	F(2, 231) = 3.22	0.042
4	<code>plaglog_bkl</code> , <code>plaglog_pc</code>	F(2, 234) = 6.84	0.001
5	<code>plaglog_bkl</code> , <code>plaglog_pc</code>	F(2, 231) = 5.17	0.006
6	<code>plaglog_bkl</code> , <code>plaglog_pc</code>	F(2, 234) = 6.91	0.001
7	<code>plaglog_bkl</code> , <code>plaglog_pc</code>	F(2, 233) = 9.44	0.000
8	<code>plaglog_bkl</code> , <code>plaglog_pc</code>	F(2, 236) = 8.88	0.000
9	<code>plaglog_bkl</code> , <code>plaglog_pc</code>	F(2, 236) = 4.22	0.016

Table 7

Variable	1	2	3	4	5	6	7	8	9
plaglog_sm	0.019151 (0.413)	0.013843 (0.608)	0.017903 (0.441)	0.010317 (0.705)	0.007164 (0.782)	0.012513 (0.649)	0.008363 (0.751)	0.011647 (0.672)	
plaglog_jklp	-0.00562 (0.910)	-0.09439* (0.092)	-0.01774 (0.700)	-0.09057* (0.088)					-0.10281* (0.085)
plaglog_spklp	0.668436** (0.000)	0.317062** (0.000)	0.642354** (0.000)	0.213503** (0.004)					0.438921*** (0.000)
plaglog_dklp	-0.01183 (0.843)	-0.17358** (0.008)			0.092656 (0.154)	-0.07285 (0.214)			-0.14041** (0.046)
plaglog_skip	-0.02466 (0.568)	0.049669 (0.304)			0.072471* (0.088)	0.064227 (0.152)			0.018822 (0.714)
plaglog_tg	0.01245 (0.679)		0.013868 (0.642)		0.042704 (0.198)		0.049089 (0.144)		
plaglog_tl	-0.04736 (0.105)	-0.0378 (0.206)	-0.04656 (0.109)	-0.04159 (0.167)	-0.07091** (0.029)	-0.04931 (0.104)	-0.07837** (0.017)	-0.05221* (0.084)	
plaglog_klm	0.722431*** (0.000)	0.389301*** (0.000)	0.722379*** (0.000)	0.376593*** (0.000)	0.660216*** (0.000)	0.430595*** (0.000)	0.630223*** (0.000)	0.423287*** (0.000)	
plaglog_sws	0.064096** (0.044)		0.065191** (0.038)		0.054845 (0.121)		0.051756 (0.147)		
plaglog_cp	0.272179*** (0.000)	0.290292*** (0.000)	0.27669*** (0.000)	0.278047*** (0.000)	0.327691*** (0.000)	0.320173*** (0.000)	0.319044*** (0.000)	0.304388*** (0.000)	
plaglog_kscm	-0.87938*** (0.000)		-0.878*** (0.000)		-0.50447*** (0.000)		-0.36262*** (0.000)		
w	-0.03245 (0.202)	-0.04072 (0.168)	-0.03274 (0.197)	-0.04239 (0.156)	-0.03379 (0.235)	-0.0392 (0.195)	-0.0331 (0.252)	-0.03978 (0.188)	-0.03332 (0.294)
c	-0.009 (0.855)	-0.13452** (0.013)	-0.00457 (0.924)	-0.12034** (0.026)	-0.05291 (0.334)	-0.14064** (0.011)	-0.09229* (0.086)	-0.13827** (0.011)	-0.23895*** (0.000)
u	0.179489*** (0.000)	0.176409*** (0.000)	0.185594*** (0.000)	0.165354*** (0.000)	0.181541*** (0.000)	0.158857*** (0.000)	0.166776*** (0.000)	0.147612*** (0.000)	0.164994*** (0.000)
plaglog_bkl	0.14172** (0.039)	0.267785*** (0.001)	0.133288** (0.048)	0.277854*** (0.000)	0.234307*** (0.002)	0.290585*** (0.000)	0.307923*** (0.000)	0.310771*** (0.000)	0.201113*** (0.010)
plaglog_pc	-0.04831 (0.320)	-0.00344 (0.951)	-0.06212 (0.163)	-0.0136 (0.792)	-0.01426 (0.773)	0.032402 (0.525)	0.048313 (0.293)	0.041467 (0.385)	-0.07046 (0.223)
_cons	2.229925** (0.031)	0.830202 (0.450)	2.34429** (0.021)	0.76888 (0.480)	2.159829* (0.058)	0.904722 (0.397)	1.658162 (0.147)	0.754418 (0.478)	5.266004*** (0.000)

P-values are in brackets below each coefficient. *** Indicates significance at $\alpha = 0.01$, ** at $\alpha = 0.05$, * at $\alpha = 0.10$.

Table 8

2SLS Results for the Demand Equation

Variable	1	2	3	4	5	6	7	8	9
plag_bklp	-1.61334 (0.097)	-0.97315 (0.070)	-1.54046* (0.098)	-0.95647* (0.058)	-1.0792* (0.081)	-0.87754* (0.074)	-0.6591 (0.123)	-0.66646 (0.114)	-0.63884 (0.286)
plaglog_sm	0.089184 (0.132)	0.068076 (0.189)	0.086885 (0.131)	0.068496 (0.182)	0.061333 (0.235)	0.062937 (0.214)	0.062992 (0.199)	0.062403 (0.204)	
plaglog_jklp	0.108707 (0.327)	-0.02211 (0.834)	0.074325 (0.470)	-0.01365 (0.890)					-0.02839 (0.778)
plaglog_spklp	1.014271 (0.146)	0.254606 (0.303)	0.954156 (0.125)	0.262303 (0.142)					0.168326 (0.590)
plaglog_dklp	0.130701 (0.356)	-0.01769 (0.911)			0.236335* (0.093)	0.078423 (0.484)			0.075199 (0.622)
plaglog_sklp	-0.09483 (0.351)	0.029568 (0.753)			0.060399 (0.545)	0.052801 (0.571)			-0.00846 (0.919)
plaglog_tg	-0.03771 (0.605)		-0.02991 (0.678)		-0.00558 (0.938)		-0.02017 (0.758)		
plaglog_tl	0.056793 (0.477)	0.080675 (0.148)	0.060988 (0.439)	0.080794 (0.147)	0.065142 (0.371)	0.078925 (0.155)	0.095088 (0.137)	0.086954 (0.105)	
plaglog_klm	0.791831 (0.271)	-0.01028 (0.963)	0.723047 (0.298)	-0.0238 (0.907)	0.321368 (0.448)	-0.01206 (0.956)	-0.02459 (0.930)	-0.07277 (0.700)	
plaglog_sws	0.065469 (0.476)		0.070967 (0.432)		0.025771 (0.728)		0.004148 (0.950)		
plaglog_cp	0.706591** (0.023)	0.55065*** (0.010)	0.703246** (0.020)	0.540001*** (0.006)	0.618513** (0.015)	0.543713** (0.011)	0.484427** (0.012)	0.481107*** (0.010)	
plaglog_kscm	-1.40445 (0.126)		-1.24448 (0.153)		-0.50862 (0.178)		-0.08491 (0.691)		
w	-0.02659 (0.690)	-0.01394 (0.813)	-0.02457 (0.708)	-0.01331 (0.821)	-0.01157 (0.845)	-0.00944 (0.870)	0.002651 (0.961)	0.001051 (0.985)	0.006309 (0.913)
c	-0.20351* (0.084)	-0.31737** (0.026)	-0.21327* (0.053)	-0.31975** (0.016)	-0.2438** (0.041)	-0.30103** (0.031)	-0.29515** (0.013)	-0.29967** (0.022)	-0.35448* (0.064)
u	0.323681 (0.131)	0.2281 (0.109)	0.330024 (0.118)	0.218738* (0.091)	0.259446 (0.102)	0.208912* (0.094)	0.159654 (0.160)	0.161666 (0.130)	0.099008 (0.478)
_cons	7.436744** (0.035)	4.98341** (0.023)	7.047521** (0.036)	4.949246** (0.019)	6.841528** (0.024)	5.216632** (0.018)	5.629671** (0.030)	5.305575** (0.011)	7.155238* (0.067)

P-values are in brackets below each coefficient. *** Indicates significance at $\alpha = 0.01$, ** at $\alpha = 0.05$, * at $\alpha = 0.10$.

Table 7 shows the results for the first stage results for the demand equation. Seven variables are consistently significant: the lagged log(prices) of Sneaky Pete's key lime pie, the Knoll lo mein, the Crimbo pie, the Knob sausage chow mein, and Boris's key lime, and the dummy variables for the Crimbo season and the game update. As this is a log-log model, the coefficients represent elasticities, except for the dummy variable coefficients. It is interesting to note that the coefficients for the lagged log(price) of Sneaky Pete's key lime pie are consistently positive, ranging from 0.21 to 0.67. In contrast, there are four other instances when a coefficient of the lagged log(price) of a key lime pie is significant, and in three of these instances the coefficient is negative with a magnitude ranging from -0.09 to -0.14. This is likely a reflection of the dual nature of the key lime pies: in one sense they are complements, but in another sense they are substitutes.

The results for the second stage of the demand equation are shown in Table 8. As expected, the coefficient for the logarithm of the price variable is negative and significantly so in six of the nine cases. The values of the significant coefficients range from -0.88 to -1.61, indicating that for every 10% increase in the price of Boris's key lime pie, the quantity demanded decreases by 9 to 16 percent.

Unfortunately, there are only two other variables whose coefficients are consistently significant. This may be the result of many of the variables working through the own price estimates, as seven variables were consistently significant in the first stage. The coefficient of the logarithm of the lagged price of Crimbo pies is significantly positive, which is in line with expectations. The values of the significant coefficients range from 0.48 to 0.71. This indicates that Crimbo pies are a fairly good substitute for Boris's key lime pie. The other consistently significant coefficient is the Crimbo season dummy variable's coefficient. This coefficient is significantly negative, suggesting that less expensive or higher quality substitute goods are available during the Crimbo season, decreasing the demand for Boris's key lime pie. This is in line with expectations. The values of the significant coefficients range from -0.20 to -0.35. The constant term is also consistently significant and positive. This finding may be a result of the lack of an income variable included in the model, as an increase in income can result in an increase in demand, assuming the income effect dominates.

The remaining coefficients are not consistently significant, but deserve some consideration nonetheless. Generally, the coefficients for the logarithms of lagged prices of substitute goods including the key lime pies are positive, which is in line with economic theory. The tofurkey gravy, the spaghetti with skullheads, and the knob sausage chow mein appear to be weak substitutes, and so are excluded from some of the regressions. The key lime pies are a particularly interesting case, as in some sense, they are both complementary and substitute goods, as previously discussed. To account for this particularity, some regression exclude all of the key lime pies while others include only some of the key lime pies. Jarlsberg's and Sneaky Pete's key lime pies are grouped together as each of these gives the player a key upon consumption. These pies are closer to being complements to Boris's key lime pie. The digital and star key lime pies are grouped together because a player must consume many of these pies in order to build the

required keys. These pies are closer to being substitutes to Boris's key lime pie. Though no particular sign dominates the coefficients of either of these groups in the second stage, the coefficient for the logarithm of the lagged price of the digital key lime pie is significantly positive in the case 5 regression. This is not a particularly rigorous result, but it is in line with economic theory.

Though none of the coefficients for the logarithm of the lagged price of the complement good are significant, all of the coefficients are positive. This is contrary to standard economic theory. A possible reason for this result is that the spice melange is a highly valued item – its mean price is two factors of magnitude higher than the prices of the other items being considered. Thus, if a player were to use a spice melange, it is more likely that he or she would consume foods with higher Adventure/Fullness ratios than Boris's key lime pie with his or her extra Fullness points.

The coefficients for the weekend dummy variable are mixed: there are six negative coefficients and three positive coefficients. This is interesting, as one would assume that an increase in economic actors would result in an increase of the quantity demanded. However, this seemingly straightforward effect cannot be verified with this econometric analysis.

Table 9
Supply Equation Cases

Case	Description
1	All complements, substitutes, key lime pies, and inputs are included in the model.
2	All complements, substitutes, and key lime pies are included in the model. The pie crust input is not included.
3	All complements, substitutes, and key lime pies are included in the model. The Boris's key lime input is not included.
4	All complements, key lime pies, and inputs are included in the model. Only the best substitutes are included*.
5	All complements and key lime pies are included in the model. Only the best substitutes are included*. The pie crust input is not included.
6	All complements and key lime pies are included in the model. Only the best substitutes are included*. The Boris's key lime input is not included.
7	All complements, substitutes, and inputs are included in the model. Only the digital key lime pie and the star key lime pie are included.
8	All complements and substitutes are included in the model. Only the digital key lime pie and the star key lime pie are included. The pie crust input is not included.
9	All complements and substitutes are included in the model. Only the digital key lime pie and the star key lime pie are included. The Boris's key lime input is not included.
10	All complements, substitutes, and inputs are included in the model. No key lime pies are included in the model.
11	All complements and substitutes are included in the model. No key lime pies are included in the model. The pie crust input is not included.
12	All complements and substitutes are included in the model. No key lime pies are included in the model. The Boris's key lime input is not included.

The best substitute good for each minimum level requirement is chosen. These goods are: the tofurkey leg, the knoll lo mein, and the Crimbo pie.

Finally, the coefficients for the game update dummy variable are all positive, but only two of them are significant at $\alpha = 0.10$. However, setting $\alpha = 0.15$, seven of the

coefficients are significant. The values of these seven coefficients range from 0.16 to 0.33. This suggests that the Cooking Changes game update had an overall positive effect on demand, though the effect is imprecisely measured. The imprecision is likely the result of the missing income variable, as the game update likely resulted in increased income. It could also be the result of some players responding more slowly to the changes than others, as some players are more serious gamers while others play more recreationally.

Twelve cases are considered for the supply equation, as seen in Table 9. As with the demand equation cases, each case is a different specification for the supply equation. Again, the hope is that the own price effect, as well as other effects, are consistent across specifications. Cases 1, 4, 7, and 10 are equivalent to the demand equation cases 1, 2, 5, and 7, respectively. The cases in between remove one of the two inputs, each in turn. For instance, case 2 has the same specification as case 1 except the lagged log(price) of the pie crust input is excluded. Similarly, case 3 has the same specification as case 1 except the lagged log(price) of the Boris's key lime input is excluded.

Table 10
Supply Equation Instruments

Case	Instruments	F Statistic	p-value
1	plaglog_sm, plaglog_jklp, plaglog_spklp, plaglog_dklp, plaglog_sklp, plaglog_tg, plaglog_tl, plaglog_klm, plaglog_sws, plaglog_cp, plaglog_kscm	F(11, 229) = 16.35	0.000
2	plaglog_sm, plaglog_jklp, plaglog_spklp, plaglog_dklp, plaglog_sklp, plaglog_tg, plaglog_tl, plaglog_klm, plaglog_sws, plaglog_cp, plaglog_kscm	F(11, 230) = 16.29	0.000
3	plaglog_sm, plaglog_jklp, plaglog_spklp, plaglog_dklp, plaglog_sklp, plaglog_tg, plaglog_tl, plaglog_klm, plaglog_sws, plaglog_cp, plaglog_kscm	F(11, 230) = 17.24	0.000
4	plaglog_sm, plaglog_jklp, plaglog_spklp, plaglog_dklp, plaglog_sklp, plaglog_tl, plaglog_klm, plaglog_cp	F(8, 232) = 8.94	0.000
5	plaglog_sm, plaglog_jklp, plaglog_spklp, plaglog_dklp, plaglog_sklp, plaglog_tl, plaglog_klm, plaglog_cp	F(8, 233) = 9.02	0.000
6	plaglog_sm, plaglog_jklp, plaglog_spklp, plaglog_dklp, plaglog_sklp, plaglog_tl, plaglog_klm, plaglog_cp	F(8, 233) = 8.56	0.000
7	plaglog_sm, plaglog_dklp, plaglog_sklp, plaglog_tg, plaglog_tl, plaglog_klm, plaglog_sws, plaglog_cp, plaglog_kscm	F(9, 231) = 10.63	0.000
8	plaglog_sm, plaglog_dklp, plaglog_sklp, plaglog_tg, plaglog_tl, plaglog_klm, plaglog_sws, plaglog_cp, plaglog_kscm	F(9, 232) = 10.70	0.000
9	plaglog_sm, plaglog_dklp, plaglog_sklp, plaglog_tg, plaglog_tl, plaglog_klm, plaglog_sws, plaglog_cp, plaglog_kscm	F(9, 232) = 10.65	0.000
10	plaglog_sm, plaglog_tg, plaglog_tl, plaglog_klm, plaglog_sws, plaglog_cp, plaglog_kscm	F(7, 233) = 11.93	0.000
11	plaglog_sm, plaglog_tg, plaglog_tl, plaglog_klm, plaglog_sws, plaglog_cp, plaglog_kscm	F(7, 234) = 11.81	0.000
12	plaglog_sm, plaglog_tg, plaglog_tl, plaglog_klm, plaglog_sws, plaglog_cp, plaglog_kscm	F(7, 234) = 10.44	0.000

Table 10 examines the instruments used for the supply equation. Recall that all variables except Q_t are included in the first stage regression. Of these variables, the lagged log(prices) of the complements and substitutes, including the key lime pies, are excluded from the structural supply equation. As Table 10 shows, these variables are significant to the first stage regression. In other words, their correlation with P_t is strong. Additionally, they are not correlated with Q_t , as show in the structural supply equation. Thus, these variables are good instruments.

Table 11a
First Stage Results, Supply Cases 1 Through 6

Variable	1	2	3	4	5	6
plaglog_sm	0.019151 (0.413)	0.019126 (0.413)	0.020668 (0.380)	0.013843 (0.608)	0.013857 (0.607)	0.01608 (0.561)
plaglog_jklp	-0.00562 (0.910)	0.014258 (0.755)	-0.00217 (0.966)	-0.09439* (0.092)	-0.09283* (0.063)	-0.10013* (0.081)
plaglog_spklp	0.668436*** (0.000)	0.657349*** (0.000)	0.699012*** (0.000)	0.317062*** (0.000)	0.316616*** (0.000)	0.342371*** (0.000)
plaglog_dklp	-0.01183 (0.843)	-0.01947 (0.742)	-0.00496 (0.934)	-0.17358*** (0.008)	-0.17398*** (0.008)	-0.18131*** (0.007)
plaglog_sklp	-0.02466 (0.568)	-0.03745 (0.364)	-0.01316 (0.760)	0.049669 (0.304)	0.048651 (0.283)	0.084536* (0.082)
plaglog_tg	0.01245 (0.679)	0.014892 (0.620)	0.01193 (0.694)			
plaglog_tl	-0.04736 (0.105)	-0.05288* (0.065)	-0.03769 (0.193)	-0.0378 (0.206)	-0.03812 (0.194)	-0.01735 (0.562)
plaglog_klm	0.722431*** (0.000)	0.732772*** (0.000)	0.708069*** (0.000)	0.389301*** (0.000)	0.39035*** (0.000)	0.328487*** (0.000)
plaglog_sws	0.064096** (0.044)	0.063621** (0.045)	0.05646* (0.075)			
plaglog_cp	0.272179*** (0.000)	0.27063*** (0.000)	0.287405*** (0.000)	0.290292*** (0.000)	0.290168*** (0.000)	0.320758*** (0.000)
plaglog_kscm	-0.87938*** (0.000)	-0.86818*** (0.000)	-0.92643*** (0.000)			
w	-0.03245 (0.202)	-0.03197 (0.209)	-0.02994 (0.242)	-0.04072 (0.168)	-0.04068 (0.167)	-0.03672 (0.224)
c	-0.009 (0.855)	-0.00523 (0.915)	-0.03278 (0.497)	-0.13452** (0.013)	-0.13419** (0.012)	-0.19851*** (0.000)
u	0.179489*** (0.000)	0.178097*** (0.000)	0.203466*** (0.000)	0.176409*** (0.000)	0.176269*** (0.000)	0.226782*** (0.000)
plaglog_bkl	0.14172** (0.039)	0.15178** (0.026)		0.267785*** (0.001)	0.2684*** (0.000)	
plaglog_pc	-0.04831 (0.320)		-0.06313 (0.192)	-0.00344 (0.951)		-0.02879 (0.611)
_cons	2.229925** (0.031)	1.857786* (0.054)	3.435382*** (0.000)	0.830202 (0.450)	0.804947 (0.429)	2.885557*** (0.003)

P-values are in brackets below each coefficient. ***Indicates significance at $\alpha = 0.01$, ** at $\alpha = 0.05$, * at $\alpha = 0.10$.

Table 11b
First Stage Results, Supply Cases 7 Through 12

Variable	7	8	9	10	11	12
plaglog_sm	0.007164 (0.782)	0.006853 (0.791)	0.008482 (0.748)	0.008363 (0.751)	0.00983 (0.709)	0.010692 (0.695)
plaglog_jklp						
plaglog_spklp						
plaglog_dklp	0.092656 (0.154)	0.088825 (0.162)	0.112091* (0.089)			
plaglog_sklp	0.072471* (0.088)	0.069859* (0.091)	0.101941** (0.016)			
plaglog_tg	0.042704 (0.198)	0.04399 (0.180)	0.044719 (0.186)	0.049089 (0.144)	0.044891 (0.178)	0.054478 (0.117)
plaglog_tl	-0.07091** (0.029)	-0.07252** (0.023)	-0.05605* (0.086)	-0.07837** (0.017)	-0.07295** (0.025)	-0.06029* (0.074)
plaglog_klm	0.660216*** (0.000)	0.663163*** (0.000)	0.629854*** (0.000)	0.630223*** (0.000)	0.613404*** (0.000)	0.573275*** (0.000)
plaglog_sws	0.054845 (0.121)	0.055029 (0.119)	0.041351 (0.247)	0.051756 (0.147)	0.050588 (0.157)	0.029636 (0.418)
plaglog_cp	0.327691*** (0.000)	0.326769*** (0.000)	0.357985*** (0.000)	0.319044*** (0.000)	0.321602*** (0.000)	0.357327*** (0.000)
plaglog_kscm	-0.50447*** (0.000)	-0.49871*** (0.000)	-0.55192*** (0.000)	-0.36262*** (0.000)	-0.36332*** (0.000)	-0.37343*** (0.000)
w	-0.03379 (0.235)	-0.03369 (0.236)	-0.02967 (0.305)	-0.0331 (0.252)	-0.0334 (0.248)	-0.02676 (0.371)
c	-0.05291 (0.334)	-0.0511 (0.347)	-0.09674* (0.073)	-0.09229* (0.086)	-0.10595** (0.042)	-0.17321*** (0.001)
u	0.181541*** (0.000)	0.18264*** (0.000)	0.224094*** (0.000)	0.166776*** (0.000)	0.160104*** (0.000)	0.220717*** (0.000)
plaglog_bkl	0.234307*** (0.002)	0.237837*** (0.002)		0.307923*** (0.000)	0.304967*** (0.000)	
plaglog_pc	-0.01426 (0.773)		-0.0393 (0.430)	0.048313 (0.293)		0.040765 (0.391)
_cons	2.159829* (0.058)	2.051406* (0.056)	4.233594*** (0.000)	1.658162 (0.147)	2.020149* (0.064)	4.481252*** (0.000)

P-values are in brackets below each coefficient. ***Indicates significance at $\alpha = 0.01$, ** at $\alpha = 0.05$, * at $\alpha = 0.10$.

The results for the first stage of the supply equation regression are shown in Tables 11a and 11b. Six variables are consistently significant: the lagged log(prices) of Sneaky Pete's key lime pie, the Knoll lo mein, the Crimbo pie, the Knob sausage chow mein, and Boris's key lime, and the dummy variable for the game update. The dummy variable for the Crimbo season has a significant coefficient in seven of the twelve cases. As with the demand equation, the coefficients represent elasticities with the exception of the dummy variables' coefficients. Again, the coefficients for the key lime pies are neither consistently positive nor negative.

Table 12 shows the results for the supply equation. Similar to the results for the demand equation, only a small number of variables have consistently significant coefficients in the second stage. The constant is consistently significant and positive. The coefficient for the Crimbo season dummy variable is consistently significant and

negative, as it was for the demand equation. The values for the coefficients range from -0.22 to -0.31.

A particularly shocking result is that the coefficient for the logarithm of the own price is negative, though in most cases not significantly so. Only in the eleventh case is the coefficient both negative and significant at $\alpha = 0.10$. There are two main reasons that could explain the negative coefficient. First, despite the strong instruments (as seen in Table 10), the model lacks an income variable. The inclusion of an income variable as an instrument may impact the sign of the coefficient. Second, it could be that the supply of Boris's key lime pie is fairly inelastic. Remember that the players' goal is to win the game by accumulating experience, Meat, and items. It could be that a player obtains a glut of Boris's key lime pies while adventuring and has little need for them. Thus, the player could decide to sell them in the Mall, regardless of the price trends. This could result in increasing supply despite falling prices.

Table 12
2SLS Results for the Supply Equation

Variable	1	2	3	4	5	6
plog_bklp	-0.1815 (0.254)	-0.18898 (0.238)	-0.14951 (0.332)	-0.28981 (0.182)	-0.30928 (0.155)	-0.16997 (0.434)
plaglog_bkl	-0.0137 (0.919)	-0.00412 (0.976)		0.012938 (0.926)	0.02529 (0.856)	
plaglog_pc	0.125239 (0.128)		0.125443 (0.127)	0.122688 (0.136)		0.12509 (0.128)
w	0.023898 (0.658)	0.022464 (0.679)	0.024404 (0.651)	0.020787 (0.701)	0.019036 (0.726)	0.023912 (0.658)
c	-0.23418** (0.016)	-0.2638*** (0.006)	-0.21871** (0.020)	-0.26397** (0.012)	-0.29626*** (0.004)	-0.22589** (0.037)
u	0.03366 (0.646)	0.01292 (0.858)	0.025682 (0.723)	0.04896 (0.520)	0.030407 (0.687)	0.029379 (0.704)
_cons	4.559738*** (0.002)	5.17066*** (0.000)	4.18373*** (0.002)	5.244612*** (0.003)	5.918557*** (0.001)	4.353632** (0.019)

Variable	7	8	9	10	11	12
plog_bklp	-0.24727 (0.204)	-0.26396 (0.177)	-0.1622 (0.397)	-0.33581 (0.102)	-0.36804* (0.076)	-0.22832 (0.281)
plaglog_bkl	0.002475 (0.986)	0.01421 (0.917)		0.02425 (0.860)	0.039657 (0.774)	
plaglog_pc	0.12369 (0.132)		0.125224 (0.128)	0.121604 (0.139)		0.12408 (0.131)
w	0.022009 (0.684)	0.020327 (0.708)	0.024099 (0.656)	0.019465 (0.719)	0.017361 (0.750)	0.022511 (0.677)
c	-0.25227** (0.013)	-0.28403*** (0.004)	-0.22317** (0.029)	-0.27662*** (0.007)	-0.31212*** (0.002)	-0.24638** (0.021)
u	0.04295 (0.567)	0.023819 (0.748)	0.027975 (0.710)	0.055456 (0.463)	0.038949 (0.604)	0.039923 (0.603)
_cons	4.975606*** (0.003)	5.636788*** (0.000)	4.289137*** (0.009)	5.535437*** (0.001)	6.283905*** (0.000)	4.838173*** (0.007)

P-values are in brackets below each coefficient. *** Indicates significance at $\alpha = 0.01$, ** at $\alpha = 0.05$, * at $\alpha = 0.10$.

Again counter to expectations, the coefficients for the lagged logarithms of the prices of the inputs are mostly positive. However, none of the coefficients are significant, and most are far from significant. The coefficient for the weekend dummy variable also lacks significance, though all of the coefficients are positive, which is in line with expectations. As with the demand equation, this may be the result of many of the variables working through the own price estimates, as six variables were consistently significant in the first stage.

Conclusion

The purpose of this research was to demonstrate that virtual economies may be useful as research tools to study real world economic phenomena. The most attractive feature of virtual economies is that they are ideal candidates for controlled experimentation. The three main benefits of using virtual economies for the purpose of controlled experimentation were discussed. The first benefits is the availability and quality of data, the second is that data are collected as revealed rather than stated preferences while maintaining a high level of realism, and the third is the lack of real world consequences when virtual economies fail or act in unexpected ways.

Despite these benefits, studying virtual economies would not be useful if results were not both meaningful for and transferable to the real world. Some previous research, such as Castranova et al. (2008) and Lehtiniemi (2008), provide support for the idea that results from studying virtual economies are both meaningful for and transferable to the real world. This study has shown some empirical results in terms of supply and demand relationships in virtual economies, building on previous supply and demand work such as Castranova et al. (2008) and Nash and Schneyer (2004). Though most variables do not have significant coefficients, there is strong evidence that prices are negatively correlated with quantity demanded in the KoL economy. Castranova et al. (2008) found the same result in Arden's virtual economy. The temporary addition of higher quality and lower price goods to the KoL economy also significantly impacts quantity demanded. The results of the supply equation are not as strong, but this is likely due to the missing income variable or a fairly inelastic supply rather than the supply of goods in a virtual economy being fundamentally different from that of a real economy.

As this is a relatively new field of study, there are many avenues for further research. The following ideas are certainly not a comprehensive list for further study of virtual economies, but they are relevant to the results of this project. First, a test for selection bias in the Kingdom of Loathing would help support the results of this research. To date, only one study has been conducted concerning selection bias in virtual worlds – Castranova (2005) – and additional proof of the absence of its effects in virtual worlds would be valuable. Second, more large scale controlled experimentation needs to be conducted in virtual worlds. The controlled experiment by Castranova et al. (2008) is the only one of its kind as of yet, and more such experiments, especially with large sample sizes, are needed. At first, they can be used to provide evidence that controlled experimentation in virtual economies is viable. Later, they should be able to help solidify (or disprove!) real world economic theories. Third, long term studies of virtual economies

are needed. Given that this field of research is very young, no long term studies have yet been conducted. Researchers are now starting to collect data from virtual economies, so medium term studies should appear within the next few years. Long term studies will take more time, but, as with the real economy, they will be incredibly valuable. Finally, a variety of economic models, like the one used in this research, should be tested and compared: are the results for virtual economies comparable to those for real economies? If not, how are they different? A detailed exploration into the similarities and differences of real and virtual economies would be useful.

In general, the body of work in the field of virtual economic experimentation needs to be expanded, and there are many areas in which interested individuals can contribute.

References

- Alexa Internet, Inc. (2009) *Traffic Rankings: kingdomofloathing.com*. Retrieved April 17, 2009, from http://www.alexa.com/data/details/traffic_details/kingdomofloathing.com
- Asymmetric Publications, LLC. (2008) *What is the kingdom of loathing?* Retrieved April 17, 2009, from <http://www3.kingdomofloathing.com/static.php?id=whatiskol>
- Baltagi, B. H. and J. M. Griffin. (2006) "Swedish Liquor Consumption: New Evidence on Taste Change." *Panel Data Econometrics: Theoretical Contributions and Empirical Applications*. Emerald Group Publishing. 381 pages.
- Bartle, R. A. (2003) *Designing Virtual Worlds*. New Riders, Boston.
- Bertrand, M. and S. Mullainathan. (2001) "Do People Mean What They Say? Implications for Subjective Survey Data". *American Economic Review*. 91(2), 67-72.
- Best foods (adventures). (2009) Retrieved April 17, 2009, from the KoL Wiki: [http://kol.coldfront.net/thekolwiki/index.php/Best_Foods_\(adventures\)](http://kol.coldfront.net/thekolwiki/index.php/Best_Foods_(adventures))
- Blizzard Entertainment. (2008) *World of warcraft subscriber base reaches 11.5 million worldwide*. Retrieved April 17, 2009, from <http://www.blizzard.com/us/press/081121.html>
- Boris's key lime pie. (2011) Retrieved April 7, 2011, from the KoL Wiki: http://kol.coldfront.net/thekolwiki/index.php/Boris%27s_key_lime_pie
- Burke, T. (2002) *Rubicite Breastplate Priced to Move, Cheap: How Virtual Economies Become Real Simulations*. Swarthmore College. <http://www.swarthmore.edu/SocSci/tburke1/Rubicite%20Breastplate.pdf>

- Castronova, (2005) "On the Research Value of Large Games: Natural Experiments in Norrath and Camelot". *CESifo Working Paper. No. 1621*.
http://papers.ssrn.com/sol3/papers.cfm?abstract_id=875571
- Castranova, E., M. W. Bell, M. Carlton, R. Cornell, J.J. Cummings, W. Emigh et al. (2008) "A Test of the Law of Demand in a Virtual World: Exploring the Petri Dish Approach to Social Science." *CESifo Working Paper. No. 2355*.
http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1173642
- Category: Food. (2011) Retrieved March 30, 2011, from the KoL Wiki:
<http://kol.coldfront.net/thekolwiki/index.php/Category:Food>
- Category: Awesome Food. (2011) Retrieved March 30, 2011, from the KoL Wiki:
http://kol.coldfront.net/thekolwiki/index.php/Category:Awesome_Food
- Chesney, T., S. Chuah, and R. Hoffmann. (2007) "Virtual World Experimentation: An Exploratory Study". *Industrial Economics Division, Occasional Paper Series. No. 2007-21*. Nottingham University Business School.
<http://www.nottingham.ac.uk/~lizecon/RePEc/pdf/21.pdf>
- Evans, W., M. Farrelly and E. Montgomery. (1999) "Do Workplace Bans Reduce Smoking?". *American Economic Review. 89(4)*, pg 728-747.
- Fullness. (2008) Retrieved April 17, 2009, from the KoL Wiki:
<http://kol.coldfront.net/thekolwiki/index.php/Fullness>
- Goat cheese pizza. (2009) Retrieved April 17, 2009, from the KoL Wiki:
http://kol.coldfront.net/thekolwiki/index.php/Goat_cheese_pizza
- Greene, W. H. (2008) *Econometric Analysis*. 6th ed. Pearson Education, Inc. 1178 pages.
- History of loathing (2009). (2009) Retrieved April 17, 2009, from the KoL Wiki:
<http://kol.coldfront.net/thekolwiki/index.php/History>
- HP. (2008) Retrieved April 17, 2009, from the KoL Wiki:
http://kol.coldfront.net/thekolwiki/index.php/Hit_Points
- KoL Marketplace v2.0. (2010) Retrieved April 7, 2011:
<http://kol.coldfront.net/index.php/content/view/1903/146/>
- KoL Marketplace v2.0: Help and Credits. (2010) Retrieved 7 April, 2011:
<http://kol.coldfront.net/newmarket/help.php>

- Lehtiniemi, T. (2008) *Macroeconomic Indicators in a Virtual Economy*. Master's thesis in Economics. University of Helsinki.
<https://oa.doria.fi/bitstream/handle/10024/37870/macroeco.pdf>
- Linden Research, Inc. (2009) *What is Second Life?* Retrieved April 17, 2009, from
<http://secondlife.com/whatis/>
- Mankiw, N. G., R. D. Kneebone, K. J. McKenzie and R. Nicholas. (2002) *Principles of Microeconomics*. Thomson Canada Limited. 512 pages.
- Manning, W et al. (1987) "Health Insurance and the Demand for Medical Care: Evidence from a Randomized Experiment". *American Economic Review*. 77(3), p 251-277.
- Mr. Accessory. (2009) Retrieved April 17, 2009, from the KoL Wiki:
[http://kol.coldfront.net/thekolwiki/index.php/Mr. Accessory](http://kol.coldfront.net/thekolwiki/index.php/Mr._Accessory)
- Nash, J. and E. Schneyer. (2004) *Virtual Economies: An In-Depth Look at the Virtual World of Final Fantasy XI: Online*. Unpublished Manuscript.
<http://lgst.wharton.upenn.edu/hunterd/VirtualEconomies.pdf>
- Nikademus. (2009) *Full list*. Retrieved April 17, 2009, from Coldfront LLC:
<http://kol.coldfront.net/index.php/content/view/245>
- Spice melange. (2008) Retrieved April 17, 2009, from the KoL Wiki:
http://kol.coldfront.net/thekolwiki/index.php/Spice_melange
- Staiger, D. and J. H. Stock. (1997) "Instrumental Variables Regression with Weak Instruments". *Econometrica*. 65(3), p 557-586.
- The KoL Wiki. (2011) Retrieved April 7, 2011:
http://kol.coldfront.net/thekolwiki/index.php/Main_Page
- The mall of loathing. (2008) Retrieved April 17, 2009, from the KoL Wiki:
<http://kol.coldfront.net/thekolwiki/index.php/Mall>
- Tofurkey leg. (2008) Retrieved April 17, 2009, from the KoL Wiki:
http://kol.coldfront.net/thekolwiki/index.php/Tofurkey_leg
- University of Bristol. (2008) "Glossary." *The Handbook for Economic Lecturers*. Retrieved April 17, 2009, from
<http://www.economicsnetwork.ac.uk/handbook/web/glossary.htm>