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Aggregate Dynamics in a Large Virtual Economy: Prices and Real Activity in Team Fortress 2[*]

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Abstract

We examine economic activity in a large virtual economy which was designed to allow de-centralized barter as the sole exchange institution. We find that a small subset of goods emerges endogenously which act of media of exchange. Our analysis includes estimation of spot exchange rates between these numerous money goods and we develop methods which allows us to price all goods and track inflation. We then calculate nominal growth and its components. We find that per-captita real wealth is an increasing component of nominal growth. Separately, we find evidence of a certain form of nominal price ridigity– the price of an item commonly priced in a particular money good tends to move with the exchange rate of that money good. We also find that announcements made by the economic planners can induce speculation leading to localized asset price bubbles.

Keywords: Virtual economy, barter system, national income accounting, wealth measurement, price level, inflation.

JEL Codes: E01 E31 P44

1   Introduction

The object of our study is the virtual economy of Team Fortress 2 (TF2) developed and overseen by Valve Software. This economy and others like it hold great potential for researchers: millions of users engaging in billions of economic transactions involving thousands of different types of goods; the game designers are near-omnipotent social planners able to create and destroy goods

and implement policy at will; and they gather essentially complete micro data that enables precise construction of macro variables. These economies have a close parallel to "real-world" markets which have recently seen an explosion of detailed high frequency scanner data. But record keeping is still nowhere near as complete as found in virtual economies like that of TF2.

The TF2 economy has some features that are unusual, even for a virtual economy. There is no explicit currency good, and trading occurs exclusively through decentralized barter. Goods are homogeneous and of known quality (i.e. there are no "lemons" as in Akerlof (1970)). Items are also durable and do not depreciate due to "wear and tear" in the way that a physical item would. Another issue likely important is that items are indivisible and can only be exchanged in discrete quantities (e.g. it is impossible to trade half of a common currency item, the treasure key, as keys are not capable of being split). There is also a significant amount of activity that is due to a very small number of very active individuals, which we will refer to as "high net worth individuals" (HNWIs). These quirks will be leveraged in future papers to discuss the issue of the spontaneous emergence of money, the emergence of trade intermediaries, and information brokerage services by applying concepts from network theory to map the interactions between different types of user.

Our approach advances ideas presented in Castronova et al. (2009) and Castronova (2008) by implementing more rigorous economic indicators of aggregate economic behavior in a large virtual economy. But there are also some crucial differences in our work: Castronova studies Everquest II, a economy with explicit currency (gold pieces) and in-game posted-price markets available to the users, thus trade in that environment would not be considered barter or decentralized in any sense. Our work also more directly adheres to methodology commonly used in modern empirical economic techniques.

Everquest II and TF2 are far from the only such examples of large virtual worlds with economic activity: "Second Life" is an entire virtual world, complete with in-game real estate, stores, jobs, and of course other people. "World of Warcraft" has players fight monsters and each other with the hope of saving the realm from the great evil that threatens it and has players engaging in money-mediated trade with each other to facilitate this end.

Even the NYSE has made its operations completely digital. Traders physically standing on the trading floor on Wall Street are in fact conducting all of their business through computer servers located in Mahwah, New Jersey. Stock traders are now similarly employed in the business of

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exchanging zeroes and ones in a computer database, albeit with higher stakes and a much greater degree of sophistication. The NYSE and its affiliated traders have had almost 200 years to develop their institutions; who knows what commerce in virtual economies will look like once it matures.

2 Research Questions

Q1: What is the trend in real growth per-capita and how can we explain this trend?

Our primary goal is a basic macroeconomic characterization of this large virtual economy. We will examine the dynamics of real growth and explain what are the economic causes of dynamics. We also will perform a decomposition of nominal growth into its constituent components: growth of the price level, real growth, and population growth.

Q2: How do macroeconomic aggregates (e.g. the price level) respond to macro-level shocks?

An appealing consequence of the complete nature of our dataset is the ability for us to pinpoint precisely what might be causing, for example, bouts of inflation or deflation. There are also numerous exogenous policy changes and events that appear to have influenced this economy and can be detected in our indicators.

Q3: How do markets for individual items respond to micro-level shocks?

A quirk of this environment is that there are numerous unexpected events that can be taken as exogenous by market participants. For example, a number of cosmetic items were suddenly "retired", meaning they were removed from the store and new items of these types could no longer be acquired, fixing their number in the economy. We might expect this intervention to increase prices – essentially a negative shock to supply – but it is also possible that market participants' speculation "overshoots" the new (post-announcement) fundamental value.

3 Environment and Data

Team Fortress 2 is a competitive multiplayer first-person-shooter game which has two teams of typically 6 to 10 combatants vying for supremacy. Winning could result from (depending on the game mode) killing enough of your opponents (but don't worry, death is only temporary!), capturing
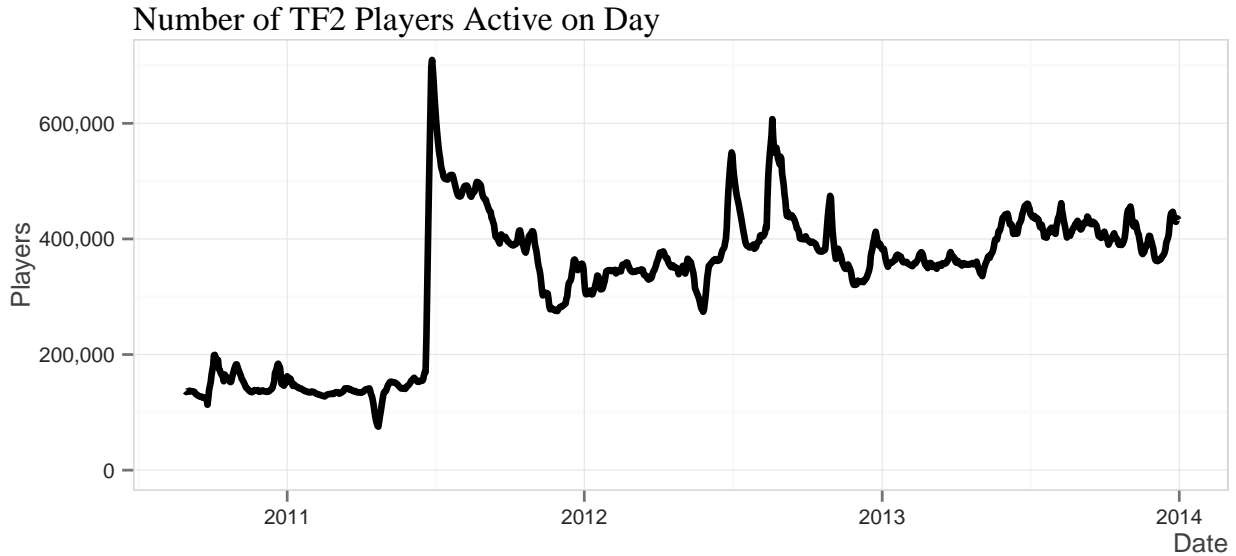
Figure 1: Daily TF2 Players

Note: Count of unique players logged into TF2 over day. Seven day moving average applied.

a briefcase full of valuable intelligence from the heart of your opponent's base and sneaking it back to your home base, or successfully pushing a cart full of explosives to your opponents base to blow them up. One round of the game typically takes ten to twenty minutes. Each player in a game chooses their character class from nine different options such as quick and agile Scout, the pro-social Medic, or the deceptive Spy and try to do their best to help their team achieve glorious victory.

3.1   Economic Environment

TF2 debuted in 2007 and initially followed the standard video game business model: players pay for a copy and can play to their hearts' content. Then, in 2008, a new dimension was added to the game: an item system which allowed users to collect virtual goods which would customize the look and play style of their characters. As people played, they would randomly receive item drops (and some special items could result from completing a list of in-game achievements), but there was no way to exchange items with each other. A September 2010 update introduced two institutions which continue on until today: a barter platform to exchange items with other players, and a virtual store where items could be directly purchased from Valve using a credit card. Figure 1 displays the number of active players on a daily basis. In November 2013 alone, there were more than 2.1 million different users that spent some amount of time playing TF2. At the end of July 2011, TF2

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went "free-to-play" (F2P), removing the requirement to purchase a game license before people are allowed to play, at which point the game generated revenue only by selling in-game items on the official store.

An item in the context of the Valve marketplace as any virtual good that can be stored in a players inventory (henceforth referred to as a "backpack") and be traded. These may include TF2 items, installation licenses for other games on Valve's digital distribution platform called Steam, and items from games other than TF2 on the Steam platform. Backpacks have finite space, but the capacity is large enough (300 item slots) that most users are unlikely feel this constraint. As well, there are "backpack expanders" that can be purchased from Valve for $.99 which loosen this constraint by granting an additional 100 item slots.

The process of successfully completing a trade is as follows: Find a trading partner through communication channels that can be internal or external to TF2, add them to your contact list, request a trade session, arrange an exchange in that session which makes both parties happy, and then execute the trade after multiple layers of confirmation. This is a quite inconvenient system for the market participants, but it represents an opportunity for inquiring economists to study actual human behavior in an environment in which we are theoretically well versed. It is important to point out that the economy *by construction* was designed to support only barter.

Our sample consists of a full log of all transactions occurring between 9 August 2011 and 31 May 2013, a 661 day interval. There were more than 70 million barter transactions, which averages out to more than 100,000 trades per day or over one trade per second. This is the primary source of the data set which we will use to do the following analysis. Across these 70 million individual transactions, over 300 million virtual items changed hands. There were 4,267,832 unique traders participating in the barter market, with the median trader conducting 4 exchanges, and with approximately one third of traders exchanging ten or more items over the sample period. Some traders participated in a large number of trades; the top ten accounts by trade count each conducted over 150,000 barter transactions.[1]

The Team Fortress 2 trading environment represents the largest dataset of a barter exchange

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[1]User Privacy: In order to protect the privacy of individuals involved in the TF2 Economy, user identities were were anonymized, timestamps masked, and any data containing unique user identifiers was held on Valve Corporation machines. Though the researchers were given access to the full log of market transactions, all other company supplied metrics removed users who marked their Steam backpacks to private.
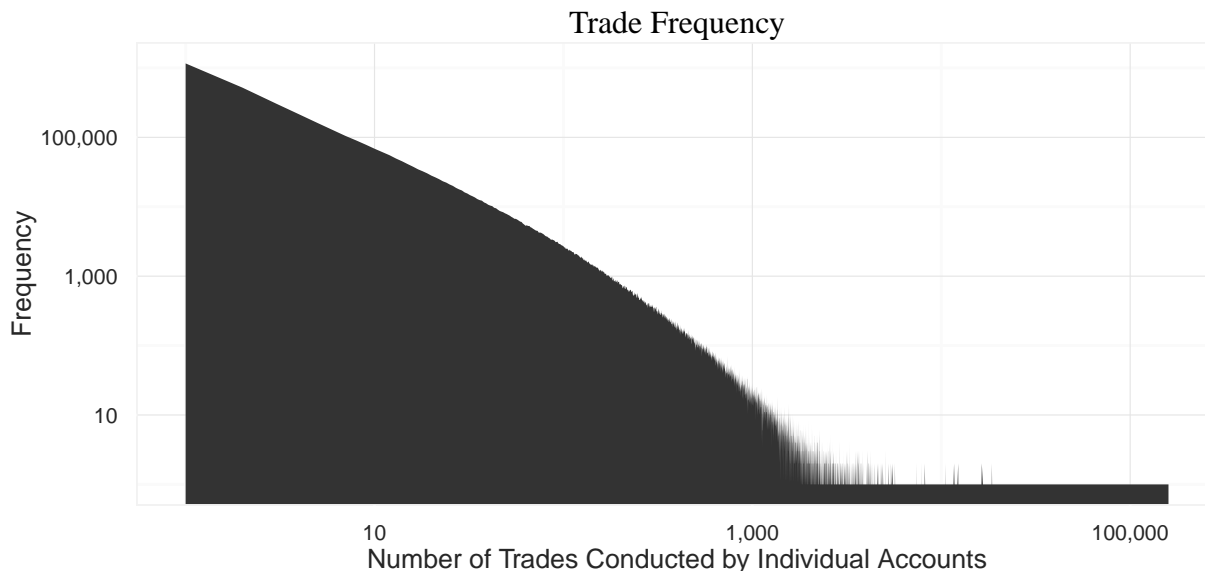
Trade Frequency

Figure 2: Histogram of User Trade Frequency

Note: Due to length of tail, top 10% of traders are not visible. Includes trading of non-TF2 game items and "Steam" game licenses. Does not include players who did not trade at least once.

market that we are aware of. This is all the more remarkable since barter markets today tend to emerge in environments which feature weak institutions and consequently have meager record-keeping.

Items in TF2 have various types. There are consumables that are used in conjunction with other items (e.g. a can of paint that can be used on a cosmetic that changes the item's color palette, or a name tag that lets the player choose a custom name for their item) and durables which can be used for as long as the owner wishes and do not undergo any sort of depreciation as a result of use. All durables have associated class restrictions; some durables can be equipped by any class and others can only be equipped by one or a few classes.

In addition, each individual item is designated one of a number of different "qualities", which serve primary to signal scarcity and characteristics of the item. These include "unique" quality (which is, counterintuitively, the most common item quality), "unusual" quality (which adds a custom effect to the item such as flames erupting from the item's surface and are overall the rarest and most sought after quality), "strange" quality (which track various statistics for the player when worn), and a few other qualities which are functionally similar to uniques.

Players can gain items from a number of different sources: random drops from playing (although

there is a cap of how many items can be received per time period from this source), direct purchase from the "Valve store" using real cash, special promotions (e.g. holidays, as a reward for completing some achievement, or as an incentive for buying another game), trading with other players, by opening crates which require a key which is then consumed along with the crate, and through a crafting system introduced in December of 2009.

From observation of the set of items most commonly used as a unit of account on independent community-created trading posts, there is evidence that the widely accepted commodity currencies include three denominations of "metals", "keys", "Bill's Hats", and "Earbuds". The three different types of metals in order of increasing value are scrap, reclaimed, and refined. There exists an in-game system that allows conversion of one denomination into another in either direction at the rate of 3 lower valued to 1 of the next higher valued. For example, anyone can convert 3 scrap metals into 1 reclaimed, then combine that reclaimed with 2 more reclaimed to create a refined, then break that refined back into 3 reclaimed. There is no cost associated with these conversions beyond the time it takes to perform them.

Metals result from scrapping (deleting) weapons from your backpack and are used in combination with other metals and items to create new items via defined recipes. Keys only come from store purchases and may be used to open crates that contain new items with various probabilities. Crates are analogous to raffle tickets; if you pay the cost of one key to open a crate, you will most likely get an item worth somewhat less than the key but there is a small chance to get a very valuable item worth much more.

Metals and keys are created and consumed regularly. Bill's Hats and Earbuds, in contrast, entered the market as promotional items given away in the past and can no longer be found or purchased directly from Valve. Their supply is bounded by the current number in existence and slowly shrinks due to people quitting the game or deleting them.

Once a player is in possession of an item, they will not lose it unless they either trade, delete, or consume the item in the case of consumables. At the end of 2012, the ability for players to sell items directly to other players for Valve store credit in an official centralized posted-price marketplace was added. This store credit is denominated in the player's local currency and is redeemable for TF2 items purchased from the Valve store as well as the purchase of licenses for other games from Valve's digital distribution platform called "Steam".

This demonstrates an important distinction between this economy and the physical world; in order to produce a good there are raw materials that necessarily must be consumed due to conservation of mass. But the production of an additional good in this virtual economy requires no more than a additional line saved to a database. There is still technically an upper bound on how many items can exist, but for practical purposes this horizon is infinite and the marginal cost of production of these goods is practically zero for Valve.

Another distinction between this environment and physical economies comes from the nature of consumption. Most real goods are actually consumed at some rate and once they are used up, are no longer usable again. This does not happen in TF2. Most consumption is of goods which are perfectly durable (with the exception of tools, but tools either result in or modify durables). We can then think of the size of this economy as being the aggregate value of the stock of durables and tools.

3.2 Data

Much of our data takes the form of logs documenting barter transactions of virtual items between two users. These are lists of transactions linked to users and the individual items associated with the trade. These data were supplied to us via a half terabyte sized relational database from which we generated observations in the form of Table 1. Each row in the transactions log represents the movement of a single item and is associated with a unique trade identifier, two unique player identifiers (one for the sender of the item and one for the recipient), a unique item-level identifier which no two items share (AssetID), and an identifier for the specific item *type* which identical items would share with each other (EconAssetClass). For example, if a player possesses two unique quality "Bill's Hats" that are otherwise identical, they would share an EconAssetClass but also each will be associated with unique AssetID that represents the specific individual item. Technically, when an item is traded its old AssetID is removed from the originating user's inventory and a new one is created for the user receiving it. Thus, we can track both individual items as well as individual classes of items, defined as items which share a type and quality which makes them functionally identical.

We present as an example Table 1. By looking at trade IDs, we can classify each individual trade into categories such as simple monetary trades or simple barter trades, as will be discussed

Table 1: Example data snippet

TradeID	PartyA	PartyB	Time	AppID	AssetID	NewAssetID	Origin	EconAssetClass
1	1203	1876	1351926000	440	38818	41361	1	100
2	4256	172	1351927010	440	39425	41362	0	194921
2	4256	172	1351927010	440	41359	41363	1	158535
3	993	8384	1351928320	440	41339	41364	0	207

in detail later. Party A and B allow us to track the trading behavior of individual traders and the AssetID and NewAssetID let us track the movements of individual items as they pass from user to user. Origin indicates which user is the recipient of the item transfer and EconAssetClass is the identifier which lets us determine the specific item type that was traded. In this fabricated example, the first trade was a one-way exchange where a player with ID number 1876 gave an item to another player with ID number 1203 and received nothing in return. The item that was given away was of type 100. The next trade involved the player 4256 giving an item of type 194921 to player 172 and receiving an item of type 158535 in exchange.

4 Estimating Prices from Barter Data

Our approach to generating prices for individual items is to define one good among the emergent currencies to be our numeraire, calculate spot exchange rates between the other currencies and our numeraire, and convert goods exchanged for those alternative currencies into the corresponding value of the numeraire. This approach gives us price estimates which allow for direct value comparisons between all items. We also generate statistics for each item including daily turnover, number of trades, and stocks.

The question of how to define which goods are used as "currencies" and which are not is not a trivial one, but this discussion is not something we shall delve into in this paper.[2] Since the different metals can be converted costlessly into each other in either direction at the rates mentioned previously, we convert all price observations involving metal into the equivalent value in terms of refined metal.

From all of the goods used as commodity currencies, we choose keys to be the numeraire. Keys

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[2]In upcoming work we will rigorously identify goods that appear to be the most "money-like" based on their characteristics in the data, but for this paper we will simply take money goods for granted and assign currency status to those items which are used as a unit of account in the major community-run pricing resources.

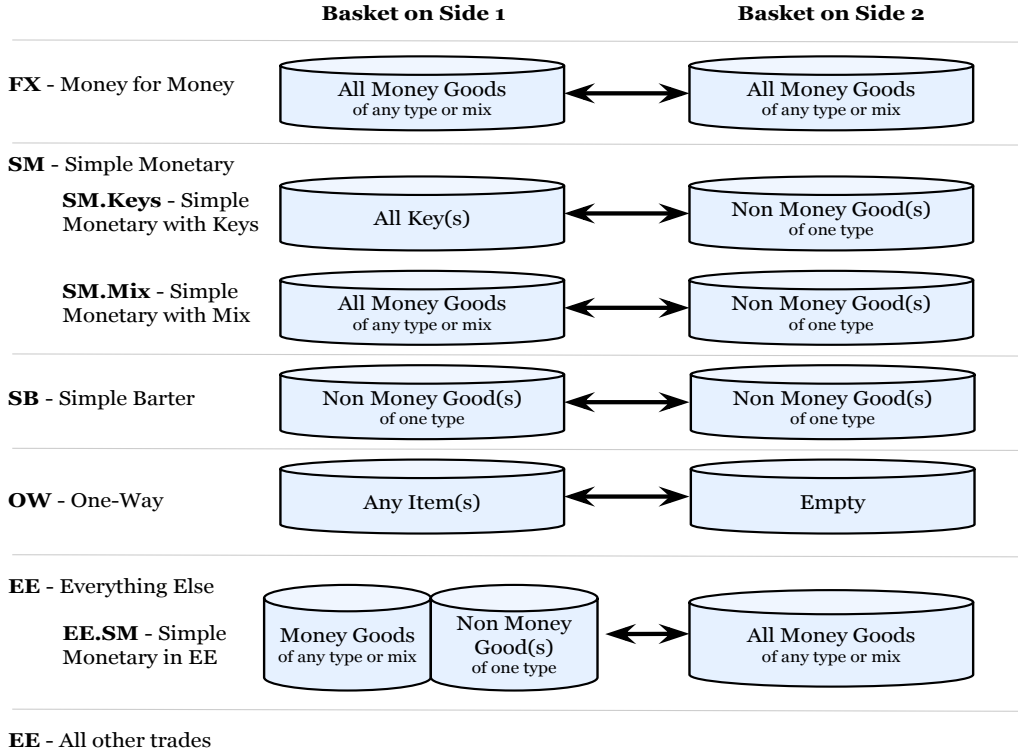|	**Basket on Side 1**	**Basket on Side 2**
FX - Money for Money	All Money Goods of any type or mix	All Money Goods of any type or mix
SM - Simple Monetary		
SM.Keys - Simple Monetary with Keys	All Key(s)	Non Money Good(s) of one type
SM.Mix - Simple Monetary with Mix	All Money Goods of any type or mix	Non Money Good(s) of one type
SB - Simple Barter	Non Money Good(s) of one type	Non Money Good(s) of one type
OW - One-Way	Any Item(s)	Empty
EE - Everything Else		
EE.SM - Simple Monetary in EE	Money Goods of any type or mix / Non Money Good(s) of one type	All Money Goods of any type or mix
EE - All other trades		

Figure 3: List of Trade Classification Types.

were selected because they appear to have the most stable value, likely due to the fact that their supply is allowed to expand as well as contract and the price is anchored to the dollar since keys can only be produced the economy through direct purchases from the Valve store at a price of \$2.49 per key. The other potential currency goods either were introduced later on (Bill's Hats and Earbuds) or displayed rapid expansion of supply (faster than the growth of population) causing instability in estimated prices.

We define a **simple monetary** (SM) trade observation as a single exchange involving a single non-currency item type and any commodity currency items. In order to use SM trades to estimate prices that are comparable to each other, prices need to be measured in a common unit, which we refer to as "synthetic keys". A synthetic key price is the equivalent key-value of a good perhaps exchanged for non-key money(s). We calculate daily exchange rates between different types of money items by looking at the subset of trades that are **money for money** (FX), which are defined as trades which have only money goods on both sides. See Figure 3 for a complete classification of all possible trade types.

By looking at these FX trades, we generate daily inter-money exchange rates as follows. Define

Q_{it}^{KM} as the quantity of *keys* traded for *metals* on date t in transaction i, where transaction i is among the subset of trades involving only metal on one side and only keys on the other. Q_{it}^{MK} is likewise the quantity of *metals* (expressed in terms of refined) traded for *keys* in the same exchange. A single metal/key exchange rate observation is thus,

$$R_{i,t}^{KM} = \frac{Q_{i,t}^{KM}}{Q_{i,t}^{MK}}$$

The daily spot metal/key exchange rate is then the median of all i exchange rate observations on date t (weighted by the number of keys in each observation), allowing us to value any quantity of metal in terms of the going rate for keys at that moment. By a similar process we derive daily synthetic key values of Bill's Hats and Earbuds. Over 910,000 transactions inform our FX sample (approximately 1,300 a day), of which 700,468 are metal-for-keys exchanges, 107,651 are Bill's Hat for some combination of metals and keys, and 104,566 involve Earbuds for some metal-key combination. Spot Bill's Hat and Earbuds exchange rates are based on trades involving keys and/or metals, converting metals into synthetic keys at the day's metal/key exchange rate.

Using these spot exchange rates to express all SM trades in terms of keys, a simple monetary price observation is as follows:

$$P_{it}^{SM} = \frac{V_{2,it}^{S.Key} - V_{1,it}^{S.Key}}{Q_{1,it}^{SM}}$$

Where $V_{2,it}^{S.Key}$ is the value, in terms of synthetic keys, of the all-money side of a SM trade, $V_{1,it}^{S.Key}$ is the synthetic key value – if non-zero – of any *currency goods* on the side of the trade that involves a non-money item, and $Q_{1,it}^{SM}$ is the quantity of the non-money good involved in the SM trade. $V_{1,it}^{S.Key}$ can be thought of as a cashier making change when a larger than necessary denomination of currency is used to make a purchase.

Over 9 million trades provide SM price observations, or an average of approximately 14,000 per day. We aggregate our sample of asynchronous price observations on time period and EconAssetClass (item type) to generate price time series for each individual variety of item. Figure 4 demonstrates our price time series for an arbitrarily chosen item, namely a stylish sombrero hat called "Old Guadalajara" which is wearable only by the Pyro character class. Notice that there are
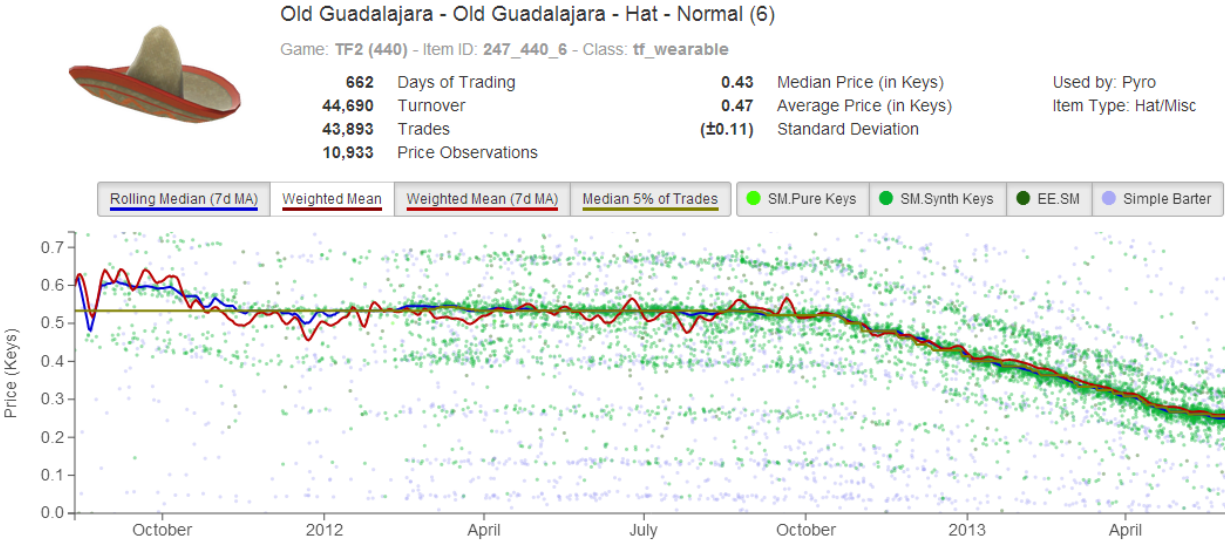
Figure 4: Price time series and meta data.

Note: A typical individual item price time series. Scatter points reflect individual transactions and their implied valuation. Multicolored lines reflect various temporal aggregate methods deriving daily prices.

discrete bands above and below the price trend line; this is a consequence of the indivisibility of the currency goods. Prior to October 2012, these bands are .1-.15 keys away from each other, which would correspond to the value of one reclaimed metal at contemporary market exchange rates.

An additional 8.5 million trades offer Simple Barter (SB) item value observations as well – trades that involve only two non-money items. However, we only use SM price observations and did not incorporate SB prices because they appear to have a more complicated valuation method than SM trades. It appears that when traders meet, if the buyer of the specific item does not or can not pay in currency items, they must pay a premium with their non-money items, meaning the trade won't be balanced in terms of value. This would simply introduce mean-zero noise to valuations if we assume that all items are equally sought after by barter traders. But if some items were relatively more sought after than other for barter exchange, there would be some item-specific fixed term that would need to be controlled for. We therefore choose to exclude SB observations from our price estimations as we determined that the number of SM trades is sufficiently large that our estimation process will be precise.

Our temporal aggregation approach assumes that each item at every moment possesses an underlying "fundamental market valuation" based on its characteristics and relevant market conditions. We then take each individual price observation as a noisy signal for that item's contemporary

fundamental value. That is, we assume SM price observations are drawn from their true values, plus some error process. It is worth mentioning that some items appear to have reasonably complex profiles, such as bimodality in price, which we take as further evidence of the economic significance of currency indivisibility.

To estimate the price of a given item on a given day, we start with a seven day window centered on that day and collect all observed SM transactions involving that item. We then clean out observations beyond the 1st and 9th price deciles as there are a large number of outliers which, for thinly traded items, can lead to a large amount of volatility. To estimate prices using a rolling average, we then apply a weighting function to these price observations based on temporal distance from the day in question and widen the time window beyond one day if necessary.[3]

A distinguishing characteristic of this environment is the constant addition of new types of items that players can buy or find. This methodology involves taking observed transactions around a given day and using those to estimate spot prices. This approach is not ideal for pricing items soon after their introduction because there will be relatively few observations. To mitigate this issue, we also develop a hedonic pricing model that imputes prices of items based on observable characteristics and supplement price estimates directly as above with estimates from this hedonic model for use in our price index. This hedonic model will be discussed further in the next section.

5   Methods

5.1   Market Capitalization

We now turn to characterizing the size and growth rate of the TF2 virtual economy. Due to the relative lack of production, GDP is not an appropriate measure for this. We instead calculate the "market capitalization" which we are defining as the total key-value of aggregate item stocks held by active players, where an player is designated "active" if they have played within 90 days. To calculate this, we take the level of existing stocks of each item in each time period and multiply them by the prevailing price in that time period, then sum over all items. We will denote aggregate

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[3]See Appendix A for more details regarding determination of appropriately wide time windows.

nominal wealth in period t as W_t and is defined as

$$W_t = \sum_{i=1}^{N_t} p_{i,t} S_{i,t}$$

where at time t there are N_t total different goods, $p_{i,t}$ is the price of good i and $S_{i,t}$ is its outstanding stock. One quirk of this economy is that a large majority of existing goods do not undergo any sort of depreciation. This means that value is constantly being created but relatively rarely being destroyed; compare this to, for example, the value created by a pig farmer. He creates value by raising pigs and selling the pork, but this value ceases to exist once the pork is eaten. Keys and metals are consumed in a similar fashion to this pork, but it is rare for other economically significant items to disappear. But this begs the question: even though item stocks should be increasing over time, is the real wealth of the average individual agent increasing along with it?

The nominal growth of all active players' inventory holdings can be written

$$W_{t+1} = G_t W_t \tag{1}$$

where W_t represents the nominal wealth and G_t represents the growth rate of nominal wealth in period t. G_t is the product of three components, population growth G_t^P, per-capita real growth G_t^R, and growth of prices (i.e. inflation) G_t^I. Thus, we can take logs of equation 1 to find (where lower cases denote log levels):

$$\Delta w_t = w_{t+1} - w_t = g_t^P + g_t^R + g_t^I \tag{2}$$

To better understand the causes of shifts in nominal aggregate wealth, we will take advantage of this decomposition but before we can do this we will need measures for each of these components.

5.2 Törnqvist Price Index

The simplest starting point for a basic price index is a Laspeyres index which uses a quantity basket fixed to a base year and estimates price increases by allowing prices to adjust in each time period:

$$P_t^{Laspeyres} = \frac{\sum_i^N p_{it}q_{i0}}{\sum_i^N p_{i0}q_{i0}}$$

However, there is a particular problem with direct implementation of a basic Laspeyres index: New items are constantly being introduced. If we choose a base period early in our timeline, we will leave out all of the items which were introduced later on which are likely to be economically important. But if we choose a base period late in our timeline, since there are some items which did not exist earlier than the base, we can have no prices for items in early periods. And, indeed, this is a significant issue for our environment. At the beginning of our data set, there are about 630 different item types traded, and at the end there are over 1600. The common alternative to a basic Laspeyres index is a Paasche index. Paasche indices suffer from a closely related issue; they take the quantity index from the current year in the denominator rather than quantities from the base year. But we can have no prices in the base time period for items which were introduced later on since we have no observed trades of goods that did not exist. Our strategy for solving this problem is twofold. First, we use a modified Törnqvist index rather than Laspeyres or Paasche. Second we use a hedonic model to estimate what prices for goods would have been just before their introduction.

Our modified Törnqvist index (Törnqvist, 1936) modeled after the way the US C-CPI-U handles its upper level price indices.[4] The Törnqvist index is superlative and built from Translog preference functions[5]. A Törnqvist price relative is as follows:

$$P_{t,t-1}^{\mathbb{T}} = \frac{P_t}{P_{t-1}} = \prod_{i=1}^n \left(\frac{p_{i,t}}{p_{i,t-1}} \right)^{\frac{1}{2}\left(\frac{p_{i,t-1}q_{i,t-1}}{V_{t-1}} + \frac{p_{i,t}q_{i,t}}{V_t} \right)}$$

where V_t is the total nominal value of all goods in the quantity basket in period t, thus $\frac{p_{i,t}q_{i,t}}{V_t}$ is the expenditure share of good i in period t. The quantity index we use to calculate was built by drawing a weekly sample of active players from the population and observing what those players were holding in their backpack. For a detailed description of our sampling methodology, please see Appendix B.

The Törnqvist index helps to avoid the problem discussed above with the simple Laspeyres:

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[4]For more details, see Cage et al. (2003) and Bureau of Labor Statistics (2014) and ILO-IWGPS (2004).

[5]See chapter 18 of the *Export and Import Price Index Manual* (2009) released by the IMF for a detailed discussion of the advantages of superlative indices
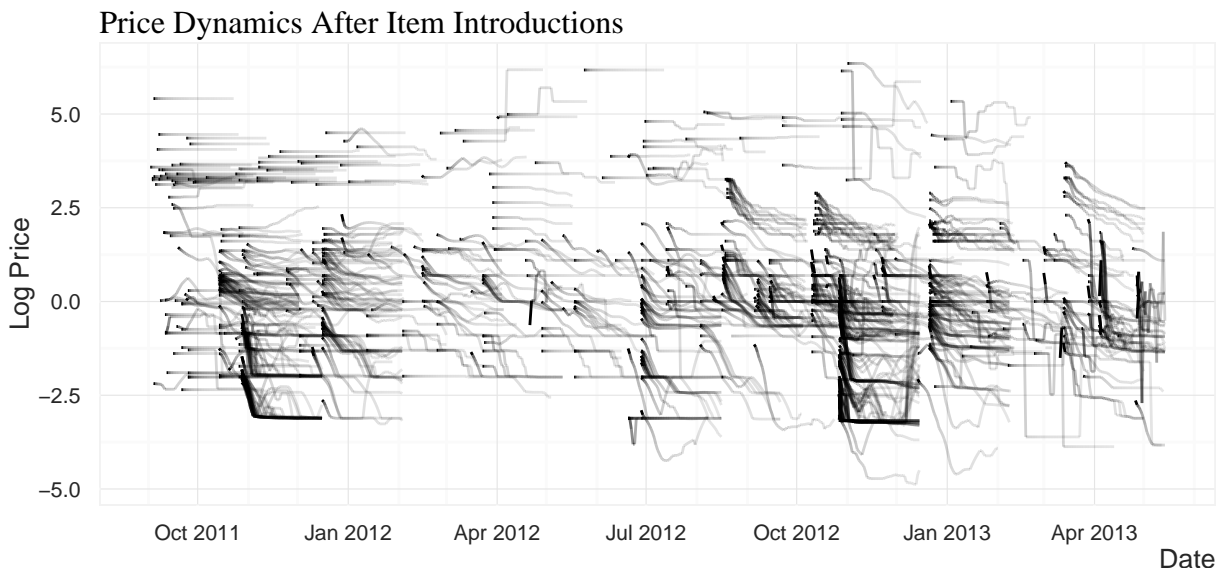
Figure 5: New item price time series.

Note: Each sparkline represents an item's price over its first fifty days.

since the base period for each calculation is the previous period, the number of new items introduced between base and current periods are minimized. As well, since the weights are value shares, new items being introduced simply decreases the weights of already existing items so the index does not increase due to increasing quantities of items. The chain Törnqvist price index from base period $t = 0$ to period T is thus:

$$\text{Chain } P_T^{\mathbb{T}} = \prod_{t=1}^{T} \left(P_{t,t-1}^{\mathbb{T}} \right)$$

One issue with our approach is due to the existence of items which are untradable - that is we observe no prices – but which appear in our representative bundle. These items certainly have a non-zero value and they do enter and leave people's inventories, but we have no choice to exclude these from our index. This is the same way that national statistical offices handle non-priced services like family household services.

5.3 Hedonic Pricing Model

Another potential issue is that newly introduced items generally exhibit a commonality in price trajectories, most new items start at a premium relative to similar items, and then steadily trade

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lower in price. Figure 5 displays the price dynamics of items starting with their introduction and tracing the time path of their log prices for the first fifty days thereafter. Log prices are used to shrink the visual distance between item time series, hopefully helping to focus on general price dynamics. Note that there are clusters of new items around Halloween and the December holidays. Items with high starting prices (log price greater than 2.5, about 12 keys or more) appear to hold their value in most cases, but items with lower initial values nearly always trend downward.

The Törnqvist price relative discussed above ignores items for which price information is not present in adjacent periods, and thus the initial premium price on most new items is not captured by the existing methodology. Though this issue is likely mitigated by the fact that new items are infrequently traded and seen in relatively few inventories when first introduced–and so their weights would be quite low–the omission of item introductions likely biases our price index downwards.

We deal with the problem of new item introductions by implementing a hedonic pricing model (Diewert, 2003; Rosen, 1974) which estimates the prices of items based on that item's characteristics compared to the characteristics of other items with known prices. A similar hedonic price imputation approach is used by national statistical bureaus to estimate prices in conditions of changes in quality. We use the hedonic method as a best estimate of the initial values of each item based on the item's observable characteristics. This is accomplished by regressing dummies for each of these characteristics interacted with time dummies on each item's prices over time. For a given time period, this gives an estimated value for each characteristic an item can have. If we apply the assumption that an item's value is approximated by the sum of values of its parts, we can estimate the price of an arbitrary an item given only its vector of characteristics. We then use these imputed prices as our best estimates for the value of items the day before they are introduced.

We impute unobserved prices via the following hedonic price model:

$$\ln(p_{it}) = \alpha + \delta_t D_t + \sum_{k=1}^{K} (\beta_{kt} \cdot x_{ik}) + \varepsilon_{it} \qquad \text{for } t = 0, 1, ..., T \tag{3}$$

For the price p_{it} of item i in period t. D_t are fixed-effect time dummies (by week), x_{ik} is a dummy indicating whether or not item i possesses item characteristic k (such characteristics are time invariant), with error epsilon which has the standard assumption of being equal to zero in expectation. Thus δ_t is the parameter on week t and β_{kt} is the parameter on characteristic k in

week t.

The different characteristics x_{ik} we include in this model are item quality, class equipability as some items can be used only by certain classes and others can be used by any class, item equip slot such as weapon or hat, and finally a dummy indicating items held by a large proportion of active players which took a value of 1 if 3% or more of users held the item and applied to less than 25% of items. We believe that these characteristics sufficiently describe different items. We are limited by the fact that a certain degree of the differentiation between items is due to non-quantifiable aesthetics (e.g., two items can be identical with respect to the observables mentioned above, but one of them might have art design that is in some sense "more attractive" and thus would command a premium), but we believe that the number of different items is large enough that these will be sufficiently averaged out when we conduct our regression.

6   Results

Our primary goal is the characterization of macroeconomic growth of this virtual barter environment. This requires the development of an aggregate price index and hedonic pricing models. Next, we present possible explanations for some of the observed macro-level behavior. We conclude with our analysis of the impact of micro-level shocks on individual items with evidence of an asset price bubble, the first bubble to be documented in a barter market as far as we are aware.

6.1   Aggregate Price Level

In Figure 6, we present the calculated chain Törnqvist price index. Overall, the price level based on representative backpack contents is relatively stable with slight deflation until approximately mid-December of 2011, when there is a surge of inflation that is possibly related to a Christmas event which brought an influx of new users into the game and introduced holiday-themed items from new crates. This is followed by a dip towards the end of the first quarter of 2012 which proved to be temporary as prices returns to their initial level and remain there for several months before seeing steady inflation until October 2012, where we see the most striking feature of our price index. Starting with the Halloween event of 2012, we see a sustained deflationary period. The overall price level returns to its initial level around March 2012 and keeps falling until the end of our sample.

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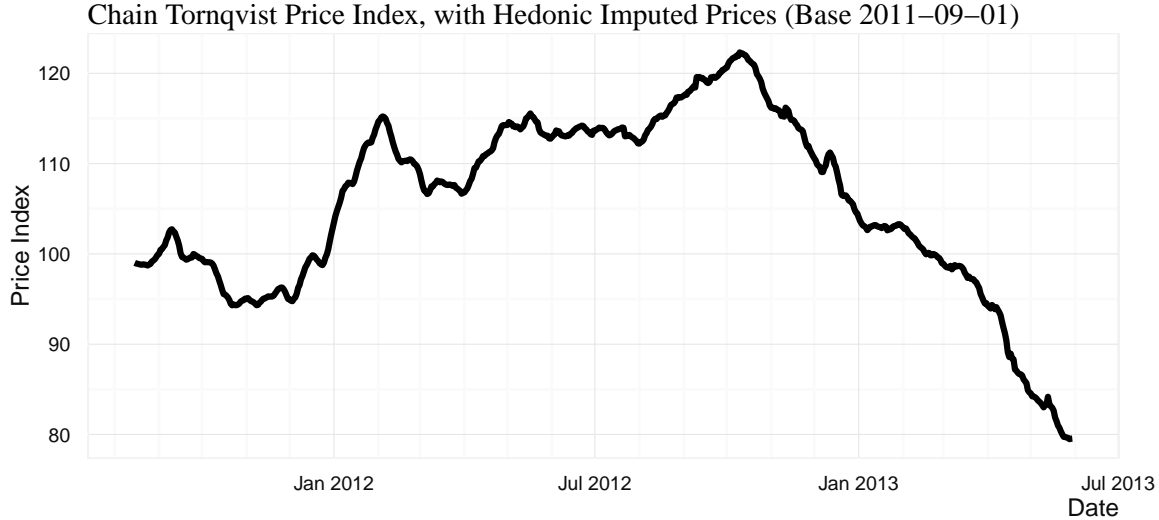Chain Tornqvist Price Index, with Hedonic Imputed Prices (Base 2011–09–01)

Figure 6: Aggregate Price Index using Chain Törnqvist with Hedonically Imputed Prices

6.2 Hedonic Model

The hedonic hypothesis postulates that for any given period, a good is a bundling of potentially time-varying price determining characteristics along with some possible aggregate price level effects that change from period to period.[6] Plotted in Figure 7 are the coefficients on the weekly fixed effect dummies D_t along with their first and second standard errors bands. These can be interpreted as an estimate for changes in the overall price level in a given week relative to the first week. Compare Figure 6 to Figure 7; with the exception of a peak in the first quarter of 2012 which does not appear in Figure 7, the dynamics are remarkably similar. These are both estimating the same thing using entirely different methodology but both tell generally the same story.

Figure 8 plots how item characteristics have evolved over the sample using the hedonic model from equation 3. In Figure 8 we see how quality premiums time series. For example, haunted items tend to have their highest premiums around Halloween (technically, we observe haunted items' least discounts around Halloween – haunted items are essentially identical to unique items, except for their text color and quality designation), but haunted quality items otherwise tend to trade at a discount relative to unique items. Unusuals clearly trade at a consistent and increasing premium relative to uniques and other qualities. Interestingly, in the weeks preceding Halloweens,

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[6]Since item-level characteristics are fairly well defined in this context – item quality, character class equipablility, and broad item type – it may be informative to run a simplified hedonic regression which eliminates time-variation in the β coefficients. Results from such a model could be interpreted as the average value placed on each observable characteristic for items in our sample and are presented in Appendix C.
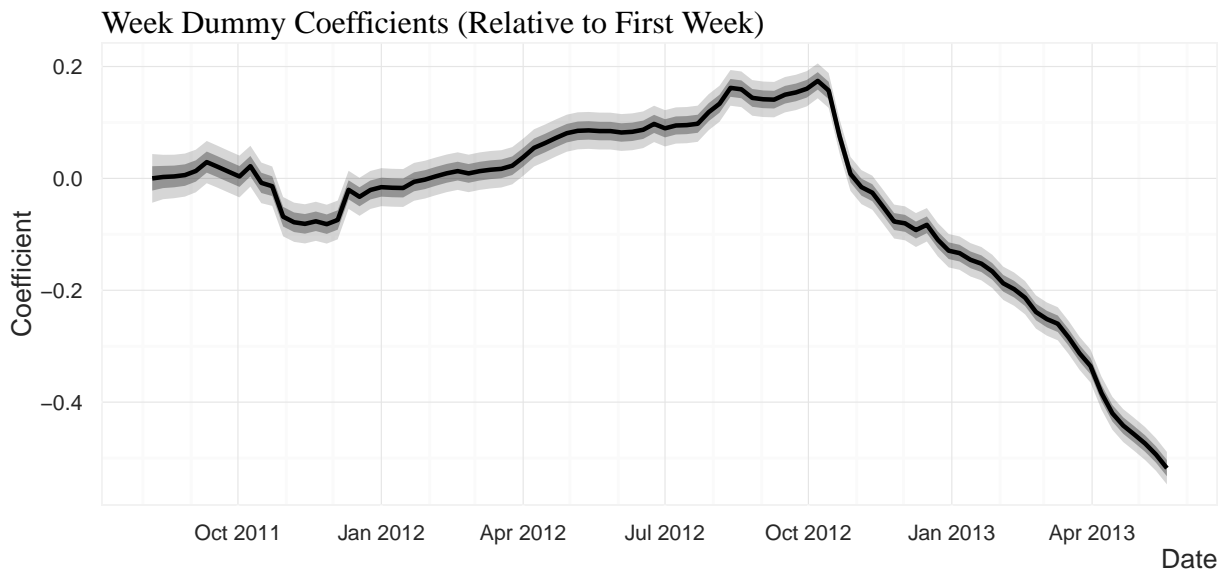
Figure 7: Time dummy estimate from simple hedonic price model.

Note: Dark and light gray ribbons reflect first and second standard error bands respectively. Coefficient estimates on time dummies from model Equation 4.

unusuals exhibit an increase in their value premium. This is possibly due to the introduction of a number of highly coveted Halloween themed visual effects (e.g. circling ghosts, cauldron bubbles, and ''Demonflame'') at this time. Vintage items exhibit a consistently increasing premium relative to uniques. Vintages are defined by their age, the plot may indicate a steadily increasing premium as items age.

6.3 Aggregate Value and Growth

Figure 9 shows the total nominal value of all items in active players' inventories (what we call "market capitalization") on a daily basis. This is calculated by taking the daily price of each item multiplied by the outstanding quantity in active players' inventories, and summed over all items. We estimate that on the last day of our sample the total value of the economy was approximately 10 million keys – or using a very conservative US Dollar value exchange rate of $2 per key (keys are available on the store at a price of $2.49, which acts as a price ceiling) – $20 million. Expanding stocks to include all TF2 items from *all users'* inventories, not just active players, market capitalization on the last day is over 50 million keys, or over $100 million. Note that towards the end of our two year sample there appears to be a decline in aggregate value. This is explained by the
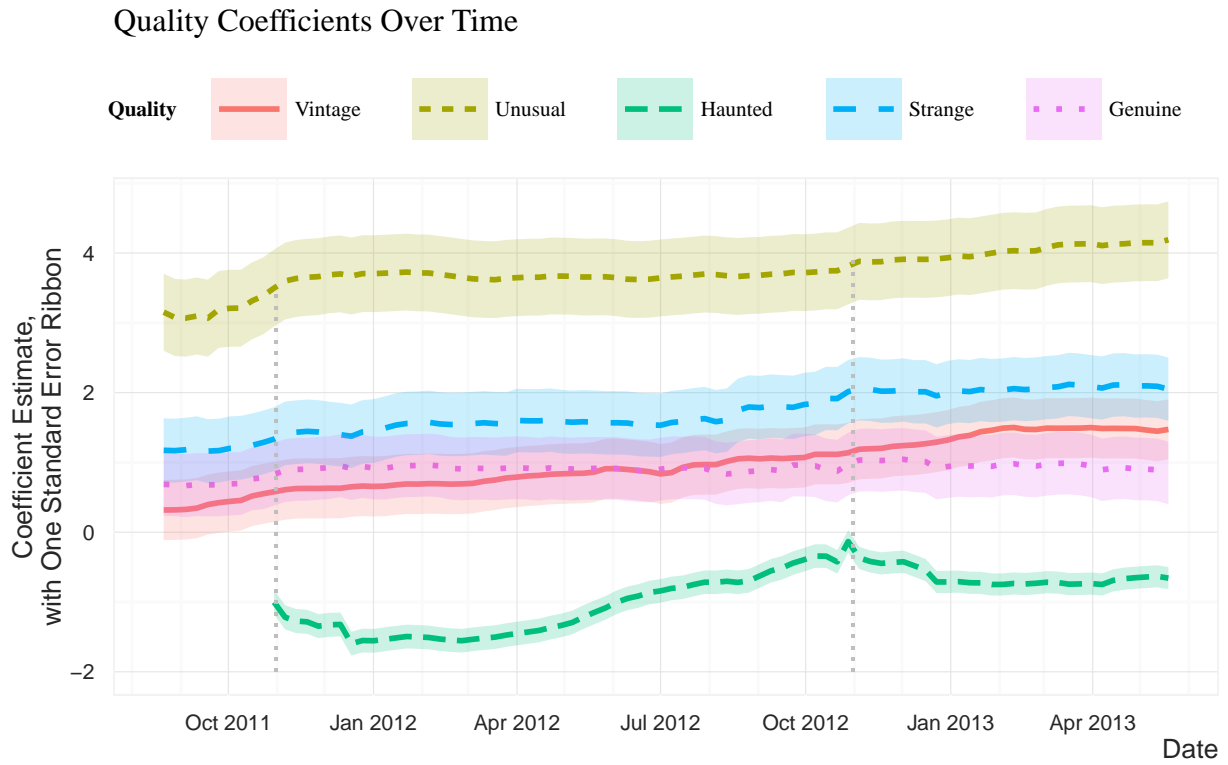
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Quality Coefficients Over Time

Figure 8: Coefficient estimates on time dummies interacted with item quality.

Note: Showing how premiums relative to unique have evolved over the trading sample. Standard error bands shows in transparent ribbons. Halloween 2011 and 2012 are indicated by vertical grey dashed lines.
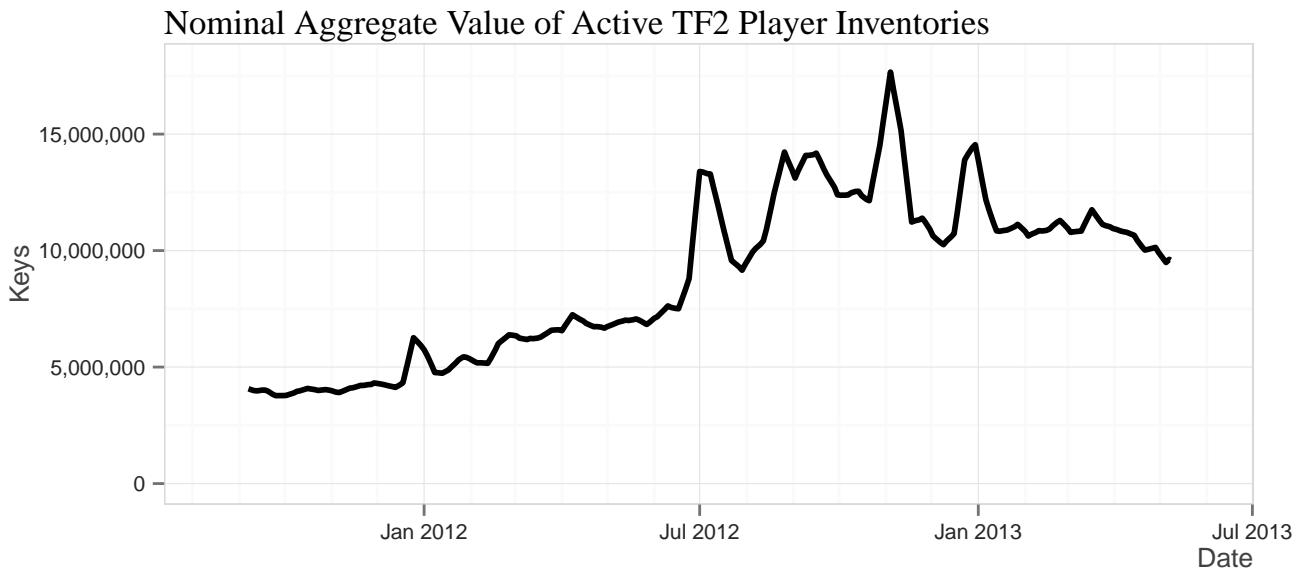
Nominal Aggregate Value of Active TF2 Player Inventories

Figure 9: Nominal aggregate value of active TF2 player inventories.

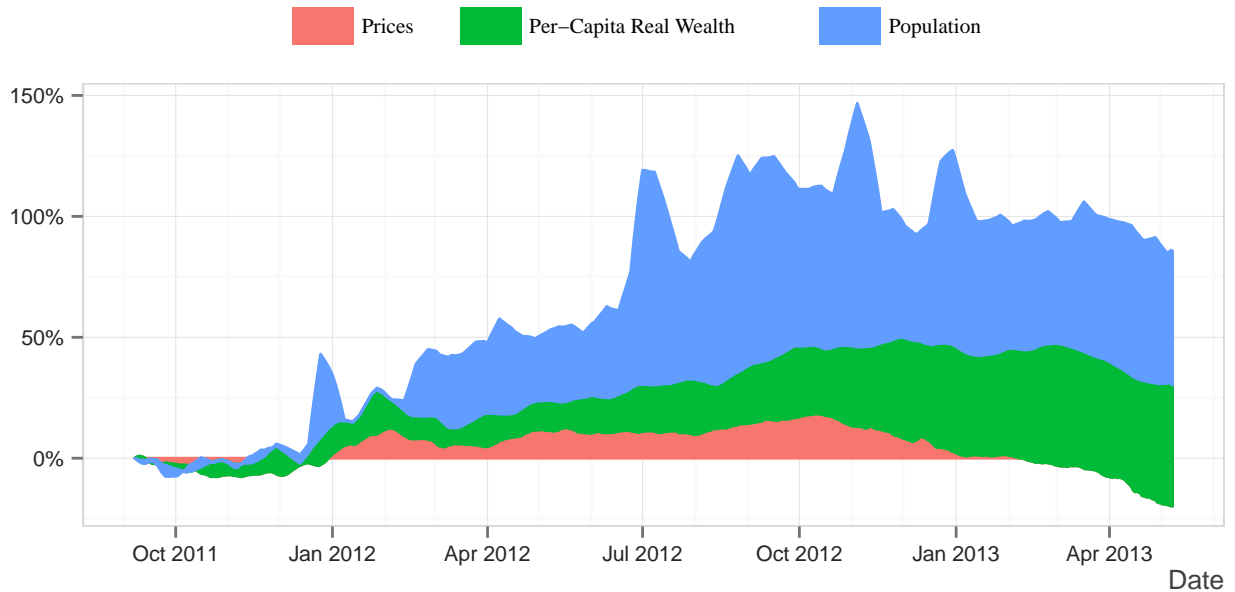*Note:* Keys are sold on the store for $2.49 each

Figure 10: Growth of nominal active player wealth

Note: Nominal growth since August 2011. Aggregate nominal value of active player wealth is the product of prices, population, and per-capita real inventory values. The natural log of nominal wealth is thus plotted as the stack of these logged components.

decline in price level causing the bulk of commonly-held items (usually traded for metals) to drop in value with respect to our numeraire.

In previous sections, we elucidated the trends of the price level and per-capita real wealth. Applying those to this decomposition along with data regarding changes in active population results in Figure 10. The levels displayed are all in percentage terms with respect to the levels in period 0. E.g. at the beginning of July 2012, the nominal economy is approximately 120% larger than it was at the beginning, of which approximately 10% can be attributed to growth in the price level, 35% of which can be attributed to growth in real per-capita wealth, and the remainder attributed to growth in the number of active players.

We see that real per-capita inventories generally displayed a slowly increasing contribution to the total growth for the duration of our sample. It also shows that practically all of the volatility displayed in Figure 9 can be explained by volatility in the population of active players and that there is actually a steady and increasing contribution to economic growth from the real per-capita component. This signifies a healthy and growing economy, even during periods which players are

rapidly switching between being active and inactive.

Prices consistently increase after January 2012 until a peak in October 2012, thereafter steadily pulling down net growth until the end of the sample. It can be seen that the contribution from prices disappears (and in fact becomes negative) on precisely the date just after January 2013 at which the price index in Figure 6 shows that the price level dips below its starting point of 100.

6.4 Nominal Rigidities and the Decline of the Price Level

Here, we present a plausible case in which this decreasing value of metals can translate to a decreasing aggregate price level. We observe that items tend to be primarily traded for a single currency. Low value items tend to trade for metals, mid value items tend to trade for keys, high value items tend to trade for Bill's Hats, and very high value items tend to trade for Earbuds as a result of the indivisibility of these currencies. It is therefore difficult to profit from currency arbitrage across "value-tiers" of items. It is this combination of price rigidities across currency denominations along with depreciation of metals that may have led to the sustained deflation we observe.

Our best explanation for the deflation towards the end of the sample is monetary and due to the quirks of a barter system with multiple de facto commodity currency goods. See Figure 11 for the daily spot exchange rates between keys and each alternative currency. Notice that decline in the price level starts at the end of 2013 – as seen in the price index in Figure 6 – syncing up with a sustained appreciation of keys against metals in Figure 11. This appreciation is quite significant: at the beginning of our sample it took a little more than two refined metals to purchase a key, but towards the end it took nearly six metals. Thus, the metal-price of keys more than doubled over this period. Also interesting to note is that the path of Bill's Hats/Key and Earbuds/Key exchange rates track each other closely (with a few exceptions near the end of the sample). This may imply that the higher-value currency goods are better substitutes for each other than the low-value metals, and is also likely due to the fixed nature of supply of these good items compared to the increasing supply of metals and keys. A more complete analysis of this potential source of depreciation is presented in Appendix D.

To illustrate this point, consider how profitable arbitrage would occur if one currency (metal) is becoming devalued relative to the other currencies but metal prices remained fixed. One would trade metals for goods, then trade those goods for non-metal currencies, then trade the non-metal

Key Per Refined Metal Exchange Rate

Keys Per Bill's Hat Exchange Rate
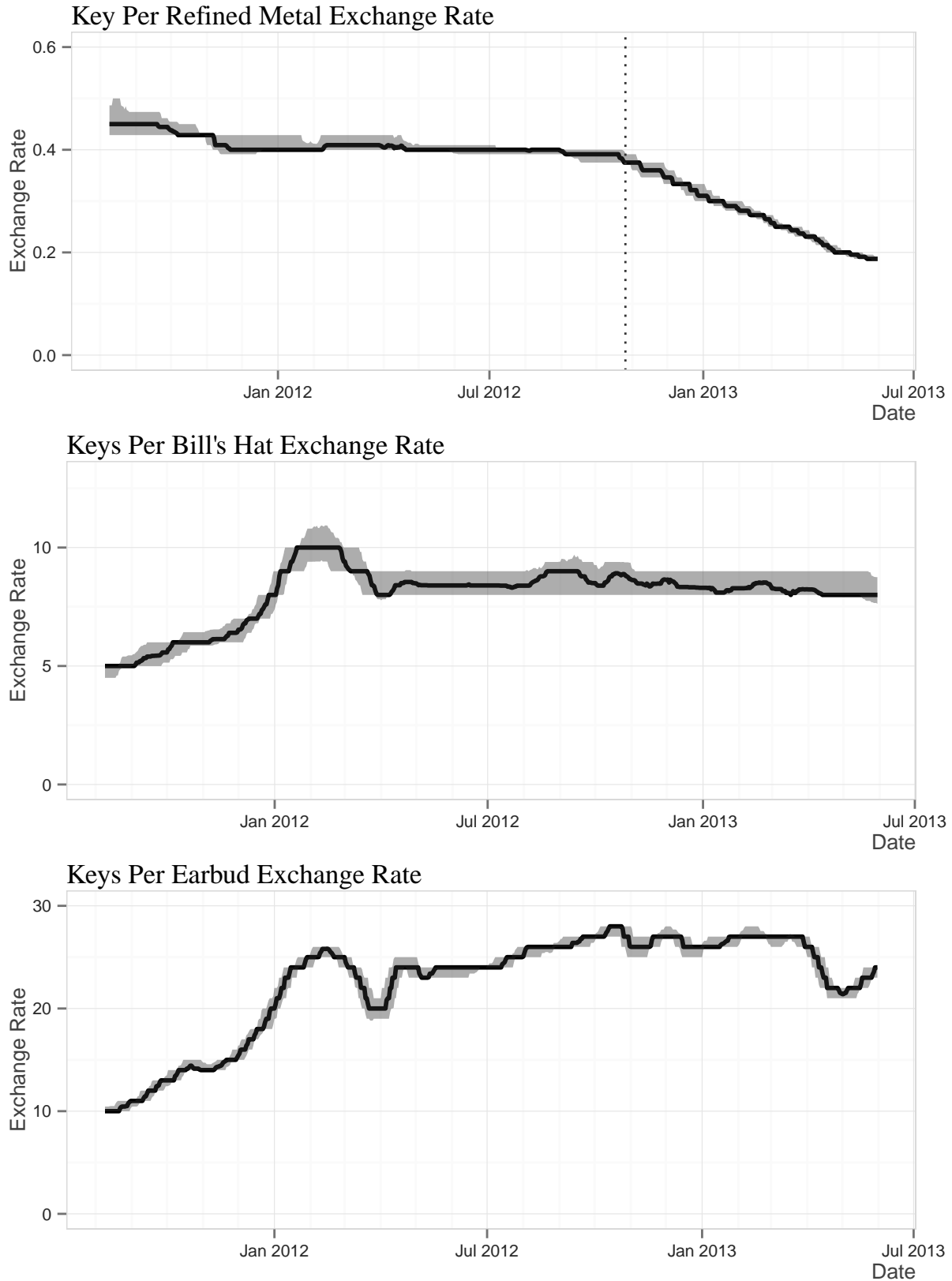

Keys Per Earbud Exchange Rate

Figure 11: Inter-money exchange rates

Note: Daily median exchange rate with three-week smoothing. Grey ribbons reflect first and third quartiles of observed daily exchanges, meaning 50% of trades occurred within gray ribbon. 31 Oct 2012 indicated by a black dotted line in the top figure.

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currencies back for more metal than they started with. This is only worth it if costs associated with trading the goods for non-metal currency is lower than the surplus from completing the cycle.

If these search and transactions costs too high enough, it is not worth it to engage in the arbitrage that would keep prices constant across all currencies. We see that as metal-key exchange rates decline and the value of metal to decreases, this does not appear to fully translate to the metal-price of metal-denominated items. Indeed, we see that for most metal-denominated items, their key-prices fall at precisely the same rate as the rate of depreciation of metal. Thus, as the key-price of metals drops, the key-prices of metal-denominated items tend to drop with it. This leads to the component of our quantity bundle which consists of items that are primarily traded for metals to drop in lock-step with the metal depreciation. If this component of the aggregate quantity index is "large", it alone can drive large movements in our aggregate prices.

We argue that this is due to frictions imposed by a barter market. If buyers were equally willing to pay with keys as metals for the purchase any good, it is likely that the prices of goods as denominated in the more consistently valued currency would be constant and there would be an increase in the price in terms of the currency which sees a declining value. But, if most traders will only offer metals for some subset of goods because it is impractical to trade for goods which are worth a tenth of a key or less using keys or higher value currencies, such a scenario is plausible.

We now present evidence for the presence of nominal rigidities discussed above, which would imply that items which happen to be priced in terms of metals – likely due to their low value and therefore difficulty in trading with indivisible higher value commodity currencies – have their value linked to the value of metals.

We investigate this by linking the frequency that metal is used to pay for items to the price change from Oct 2012 to the May 2013. We estimate the following weighted OLS model:

$$\rho_i = \beta_0 + \beta_1 \cdot m_i + \varepsilon_i$$

In this regression, m_i represents the value proportion of SM trades for item i in which the item trades for metal and thus $1 - m_i$ is the value proportion of trades which the item was exchanged for non-metal currencies. For example, an item that *always* traded for metals would have an m_i of 1 and an item for which half of the value of trades was from metals and half was from keys, m_i would

be .5. The regression relies on value share percentages derived from October 2012 observations and these value share percentages hold a 0.95 correlation with observations in May 2013, implying that these value shares seem relatively stable over our time horizon. The dependent variable ρ_i represents the percent change of the price of item i with respect to this item's price in October 12, 2012, just before the start of the deflationary period.

The model is weighted by the total value of each item i in the month of October 2012, thus more economically significant items were given heavier weights. We only looked at items for which prices were observed in both Oct 2012 and May 2013, there were 1,288 such items. We remove observations for which percent price changes were above the 99th or below the 1st percentile, leaving 1256 items with prices in both periods.

The interpretation of this regression is straight forward: the sign of the coefficient on m_i tells us if items which were primarily traded for metals tended to undergo price increases (positive β_1) or price decreases (negative β_1) over the period of deflation which started in October 2012.

Table 2: Regression Estimates from WOLS of Price Change on the Trading Value Share of Metal.

	Dependent variable:
	Percent Change in Price
Metal Value Share	-0.1867^{***} (0.0406)
Constant	-26.0422^{***} (1.4763)
Observations	1,256
R^2	0.0166

Note: *p<0.1; **p<0.05; ***p<0.01

Our regression coefficients are reported in Table 2. It shows that a one-percent increase in the value of metal an item tends to trade in Oct. 2012 is correlated with an additional 0.18% drop in price between Oct 2012 and May 2013. Thus overall on average, items that traded 100% with metals tended to experience an 18% decrease in price compared to items which never traded for metals. This is evidence that items which trade primarily for metals tend to have a corresponding decline in price. But the decline in price is also less than the decline in the exchange rate of metals (approximately 50% from October 2012 to May 2013, as can be seen in Figure 11) which means that this is likely only a part of the whole story.
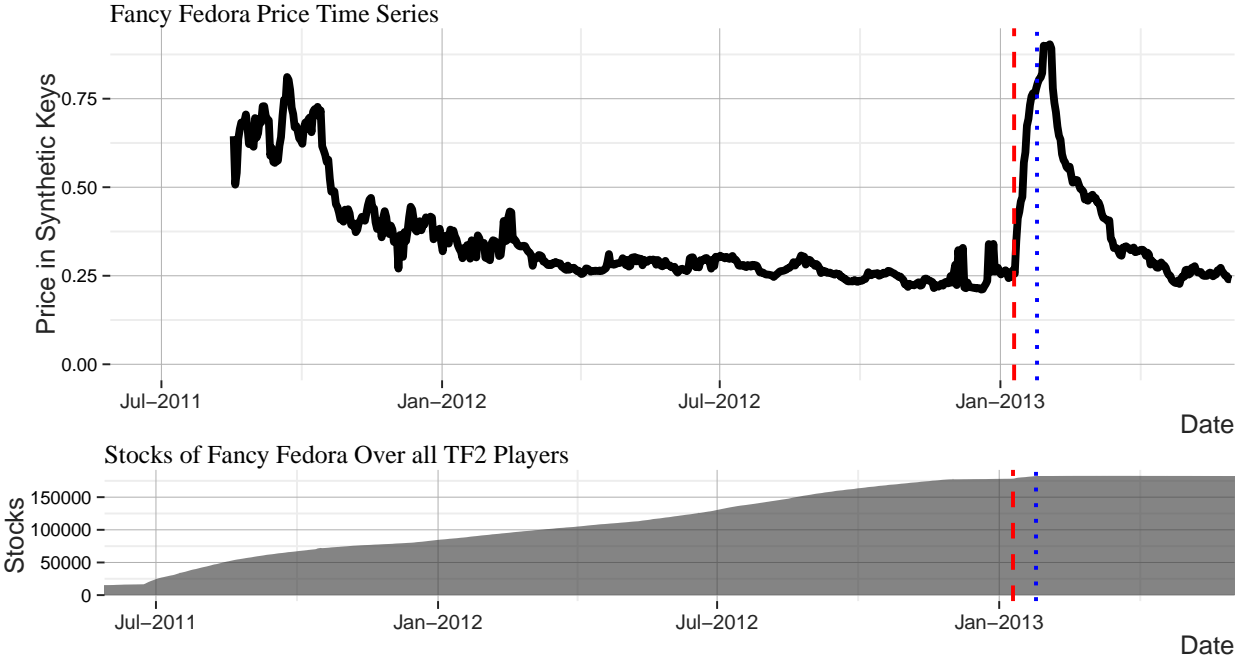
Figure 12: Price time series of the unique (normal) quality Fancy Fedora.

Notes: The date of the store retirement announcement is indicated by a dashed red line, and the actual retirement date is indicated by the second dotted line, in blue.

6.5 Response of Individual Items to Micro-level Shocks

We conclude our results with a discussion of the impact on individual items of micro-level shocks. Notice in Figure 12, the price of the Fancy Fedora starts high and over a few months drops down and stabilizes, as is typical for newly introduced items.[7] But at the beginning of 2013, there is a sudden spike in interest. This is driven by a 10 Jan 2013 announcement, as indicated by a red dashed line, that this hat and 8 others would be "retired" on 25 Jan 2013 as indicated by a blue dotted line. Retirement of these items means that they are no longer acquirable except by trading with other players and thus the total supply would be capped at the current level on 25 Jan.

This announcement led to rampant speculation on these items which drove up the price by approximately 120% over the two week time period between announcement and retirement. But this price boost ultimately proved to be temporary as the price falls almost as rapidly as it surged in the first place. This represents the first evidence of a possible speculative bubble in a barter market that we are aware of.

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[7]The price time series was generated using trailing price estimates rather than the centered prices discussed above. This was because centered prices cause price estimates to increase before the announcement which is not representative of what was happening in the market on this day.

Figure 12 also shows the stocks of Fancy Fedoras. On January 10, 2013 there were 178,400, which increased by 2.26% to 182,440 by January 25th. Our best explanation is that there was a sufficient quantity of these hats in existence to satisfy the demand for them for the purpose of durable consumption at the price of approximately 0.2 keys, but the retirement announcement caused a positive demand shock as market participants anticipated a negative future supply shock, driving up current prices (red dashed line). Soon after this negative supply shock took place (blue dotted line), it became clear that the act of fixing supply did not actually do much to shrink quantity available and – as well as the fact that there are likely a large number of close substitutes and the influx of supply by speculators after the January 10 announcement – meant that people interested in durable consumption of the item could simply buy a different hat that didn't see the price more than double. Thus, the announcement and subsequent retirement did not effectively change long run demand and had a small but positive effect on long run supply, so the price returned to its initial level and the speculators that went long on them figuratively lost their shirts.

Another item example demonstrating clear market responses to micro-shocks is the strange Scattergun, a strange-quality version of the default class weapon of the Scout. Strange quality items are notable because they record some sort of player statistic while the player uses the item (e.g. a counter that tracks total number of other players killed with the gun).

On 9 October, as shown in Figure 13 with a red dotted line, these stranges were suddenly made available from a newly introduced and particularly ubiquitous series of locked crates and found inside these crates with a probability of approximately 20%. The effect of this policy shock on supply can be seen in Figure 13. The total stock on October 9, 2012 was approximate 71,000 and had been increasing at the rate of approximately 50 per day for months. After this new crate was introduced the rate of increase of the inventory stock suddenly exploded, after one month there were more than 101,000 strange Scatterguns in existence. After three months, these stocks had doubled.

The impact of this sudden large positive supply shock can clearly be seen in the price of the gun, depicted in Figure 13. In contrast to the story of the Fancy Fedora, in which the retirement of an item did not appear to have a long lasting impact on the market supply or demand leading to long run prices being the same as before the retirement, this event obviously actually impacts the long-run supply which causes an unambiguous decrease in long-run market price. Thus, individual prices
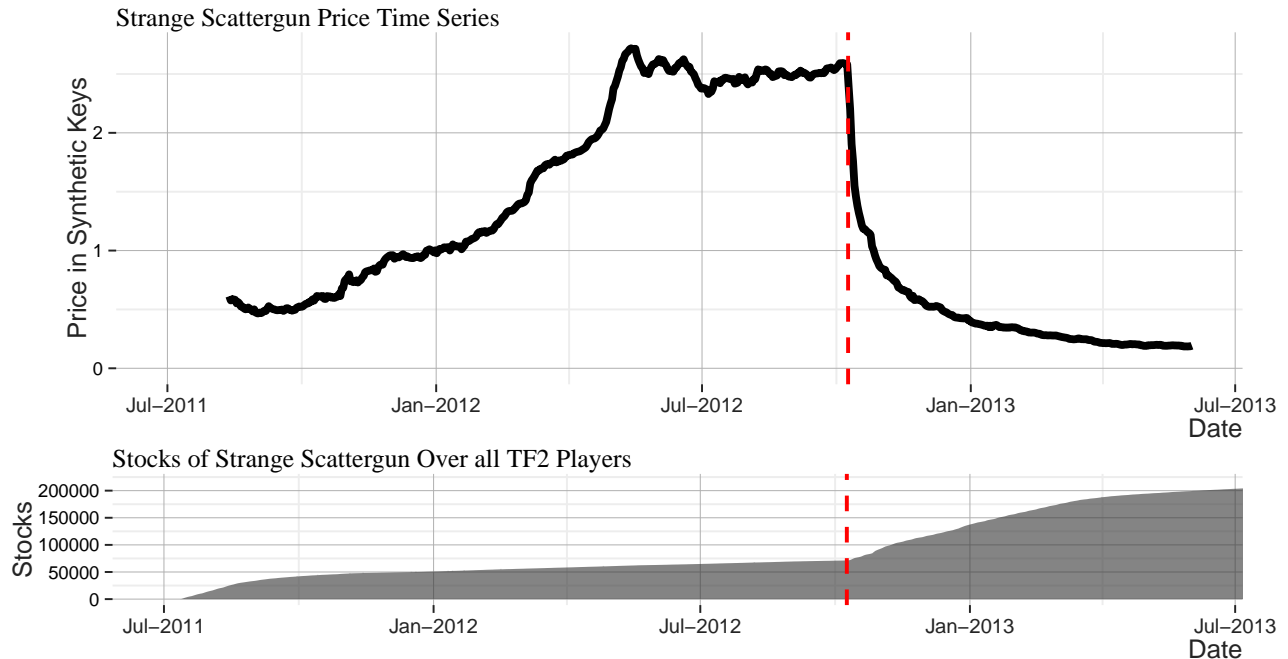
Figure 13: Price time series of the strange quality Scattergun.

Note: The red dotted line is at October 9th, the date which the item became more widely available.

in the economy do indeed appear to respond to specific micro-level shocks in the ways consistent with basic microeconomic intuition given the direction of the shocks to supply and demand.

7   Conclusion

With this work, we present an examination of an economy which is interesting for at least two reasons. First, it is a remarkably rich dataset which documents a true barter market, the likes of which have been pondered by economists for centuries. Second, it's a virtual economy consisting entirely of non-tangible goods which people nonetheless assign value to.

Our primary goal was to calculate macroeconomic growth in this novel environment and concluded that an increasing component of nominal growth was due to increases in real per-capita holdings. Per-capita real wealth displays a slow and steady growth for the duration of our sample and most of the volatility in aggregate economic value can be explained by volatility in the active player population.

We presented a hedonic pricing model which we used to impute prices for a Törnqvist price index. We show that not all classes are created equal when it comes to item values. The index

indicates that the price level tended to rise until October of 2012, at which point the price level starts declining due at least in part to the declining value of metals. We then traced the source of this depreciation of metals to a shock to both the stocks of metals and keys as well as the rate of increase of their respective supplies.[8] We then demonstrated that items which trade for metals tended to have prices that decreased as the value of metals declined, indicating possible nominal rigidities. But the price decline was less than the decline of the value of metals, so this is likely not the only thing affecting these items. Thus we did find evidence that macro-indicators responded to macro-level shocks.

Finally, we find in these virtual economies evidence of the same sorts of forces which evidently influence "real world" markets in our micro-level case studies. If a credible central authority makes some decree that could increase expectations of future prices, prices move in that direction. If there is a sudden exogenous positive supply shock in the market for a specific good, the price of that good falls. These goods are but two of many items that have been impacted by idiosyncratic shocks, and their behavior is mirrored in similar goods which were subjected to similar shocks. None of this news should be surprising, but it supports our position that other such virtual economies (which are certainly only going to become more common in the coming years) are fertile ground for further research and the fact that these virtual economies will typically have impeccable record keeping should be enough to get researchers excited.

Future work will investigate the emergence and evolution of number of fundamental market institutions in the tradition of Radford (1945), Burdett et al. (2001), and Lankenau (2001) and we will search for the origin of media of exchange and the development of trade intermediaries by mapping trade networks and behaviors of these intermediaries. In doing so, we hope to answer questions related to how much surplus such intermediary activity brings to the economy as a whole, and how is that surplus is distributed amongst various types of users, deep questions that go to the heart of classic economic inquiry[9] and are issues which many modern economists have struggled to answer empirically.

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[8]See Appendix D
[9]See Smith (1776), Jevons (1885), and Menger (1892)

References

George A Akerlof. The market for "lemons": Quality uncertainty and the market mechanism. *The Quarterly Journal of Economics*, pages 488–500, 1970.

Kenneth Burdett, Alberto Trejos, and Randall Wright. Cigarette money. *Journal of Economic Theory*, 99.1:117–142, 2001.

United States Bureau of Labor Statistics. *BLS handbook of methods*. US Department of Labor, Bureau of Labor Statistics, 2014.

Robert Cage, John Greenlees, and Patrick Jackman. Introducing the chained consumer price index. In *International Working Group on Price Indices (Ottawa Group): Proceedings of the Seventh Meeting*, pages 213–246. Paris: INSEE, 2003.

Edward Castronova. A test of the law of demand in a virtual world: Exploring the petri dish approach to social science. Technical report, CESifo working paper, 2008.

Edward Castronova, Dmitri Williams, Cuihua Shen, Rabindra Ratan, Li Xiong, Yun Huang, and Brian Keegan. As real as real? macroeconomic behavior in a large-scale virtual world. *New Media & Society*, 11(5):685–707, 2009.

W Erwin Diewert. Hedonic regressions: a review of some unresolved issues. In *7th Meeting of the Ottawa Group, Paris, May*, pages 27–29, 2003.

International Monetary Fund. Export and import price index manual: theory and practice. INTERNATIONAL MONETARY FUND, 2009.

ILO-IWGPS. Consumer price index manual: Theory and practice. 2004.

William Stanley Jevons. *Money and the Mechanism of Exchange*, volume 17. 1885.

Stephen E Lankenau. Smoke'em if you got'em: Cigarette black markets in us prisons and jails. *The Prison Journal*, 81(2):142–161, 2001.

Karl Menger. On the origin of money. *The Economic Journal*, 2(6):239–255, 1892.

Robert A Radford. The economic organisation of a pow camp. *Economica*, pages 189–201, 1945.

Sherwin Rosen. Hedonic prices and implicit markets: product differentiation in pure competition. *The Journal of Political Economy*, pages 34–55, 1974.

Adam Smith. An inquiry into the nature and causes of the wealth of nations: Volume one. 1776.

Leo Törnqvist. The bank of finlands consumption price index. *Bank of Finland Monthly Bulletin*, 10(1936):1–8, 1936.

Appendix

A   Price Weighting Methodology

We use a number of different approaches in generating weights to assign to individual observations in estimating daily prices. Broadly, these approaches fit into two categories: "Centered" and "Trailing" (or Leading).

A.1   Centered Prices Weighted Mean

To calculate an item's mean price for a specific day, we start with an interval of seven days. We collect all SM price observations from three days previous to three days into the future and remove any price observations above the 9th decile and below the 1st decile. We drop these extremes because almost all items have many price observations which are clear outliers and means are sensitive to such outliers. We then apply a triangular (or, more precisely a trapezoidal) weighting function as illustrated in Figure 14

There are initially three days on either side of the day which we are estimating prices for. Many items are very high volume and thus we have lots of price observations but for some items, there is relatively low enough volume such that even including a full week does not give us a large enough number of observations that we are confident in their prices.
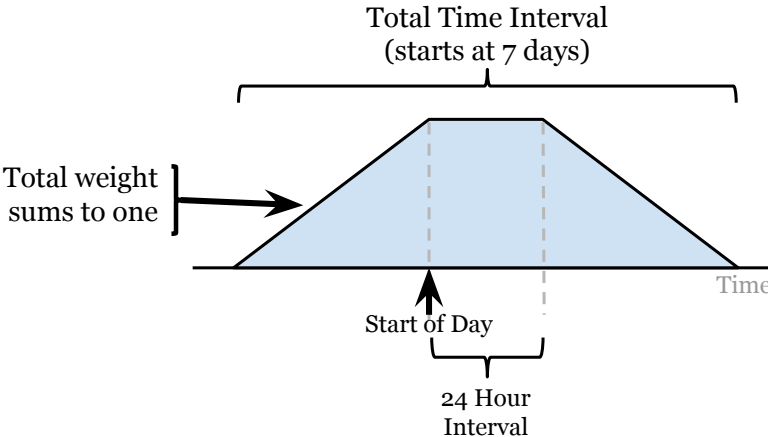

Figure 14: Weighting function

To account for this issue, we define a control system which utilizes the coefficient of variation:

$c_v = \frac{\sigma}{\mu}$, where μ and σ are the mean and standard deviation of our sample. Our control system sets a cutoff value for coefficient of variation c_v^* and we calculate the coefficient for each item in a given time period c_v^{it} and if i is true that $c_v^{it} > c_v^*$, we increase the window for that item on that day by one day and recalculate. This process is repeated until the window includes sufficient observations such that $c_v^{it} \leq c_v^*$. The cutoff we use for this process is $c_v^* = .5$ a this number appears to consistently select an appropriate window width.

B   Representative Basket Derivation Methodology

In consumer inflation indexes like CPI these quantities strive to reflect typical consumption baskets. In contrast, quantities reflect producer purchases in input producer price indexes and in the Gross Domestic Product deflator they reflect production quantities. Our quantity index reflects the bundle of goods held by a "representative player."

B.1   Methodology

These representative player inventories were generated by drawing random samples of users from the active player population, where an active player is defined as one who logged into Team Fortress 2 within ninety days of the sample date. We identify the average quantity of each TF2 item held in the sampled inventories. But there are some unique issues with our sampling in this environment due to the presence of an upper tail of inventory value distributions composed of people with very large inventory values. These HNWIs are rare enough that we almost certainly will not have a good balance of them represented in each time period's active player sample. Increasing our sample size sufficiently beyond 1% of the population is also technically infeasible given the number of active players (typically more than 250,000 each week) many of whom possess scores of items. Without adjustment, the price index could exhibit big movements from one period to the next due more to sudden shifts in the quantity index than shifts in price.

Our approach to dealing with these HNWIs is first to tag the top proportion of wealth-holding individual users as HNWIs, where we define the inventory value cutoff as a nominal inventory value above 800 keys, or approximately \$1600. If an active player is classified as a HNWI in one of these censuses, their inventories are logged each week for the entire year and they are excluded from the

non-HNWI sample for that year. These HNWI players account for approximately 0.3 to 0.4 percent of the active player population.

We then track inventories of all HNWIs each period along with the random 1% sample of *non-HNWIs*, and derive average item inventories for each group. The composition of the basket derived from these 1% samples does not fluctuate greatly from time period to time period. Finally, the HNWI and non-HNWI representative inventories are combined weighting item quantities based on each groups' relative proportion of the overall active player population at each period.[10]

All inventory data excludes individuals who have marked their "Steam Profile" as private. Of the approximately 1,500 unique active players classified as HNWIs, 255 have been excluded due to this privacy restriction on their their backpacks. Our methodology thus assumes the omission of these privacy preferring players does not significantly bias the representativeness of our HNWI and non-HNWI sample.

Once representative baskets are found for each tier, they are average together weighted by the relative proportion of each group to the overall population.

C Hedonic Estimates of Values of Item Characteristics

Equation 4 presents the hedonic model we estimate. We use this simplified version because the model with time dummies has thousands of regression coefficients, far too many to report in a single table. The full model from Equation 3, however, was used to produce Figures 7 and 8:

$$ln\left(p_{it}\right) = \alpha_t + \sum_{k=1}^{K}(\beta_k \cdot x_{it}) + \varepsilon_{it} \qquad \text{for } t = 0, ..., T \tag{4}$$

For item i in period t, price p_{it} is a function of weekly time dummies, K time-invariant item characteristics, and an error process. Table 3 shows the coefficient estimates of the hedonic regression.

All TF2 items are associated with a single "quality". We used the unique quality for our regression as it is by far the most common as the baseline, and estimates for each item are premiums or discounts relative to that item's unique version. These results suggest that vintage items have tended to trade a full 180% above more normal unique quality ones. All unique quality items that

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[10]Our representative basket derivation methodology is discussed in more detail in Appendix B

Table 3: Hedonic Price Model with Time Unvarying Characteristic Dummies

	Dependent variable:	
	log price	
Quality (mutually exclusive), Relative to Unique Quality		
Genuine	0.9035^{***}	(0.0054)
Haunted	-0.9255^{***}	(0.0077)
Other	5.5827^{***}	(0.0621)
Strange	1.9038^{***}	(0.0051)
Unusual	3.7819^{***}	(0.0042)
Vintage	1.0300^{***}	(0.0045)
Item Type (mutually exclusive) Relative to Action Items		
Cosmetic	0.4629^{***}	(0.0098)
Tool	-0.0655^{***}	(0.0111)
Weapon	-0.5792^{***}	(0.0105)
Character Class Equippablility (non-exclusive)		
Spy Equippable	0.2507^{***}	(0.0041)
Engineer Equippable	-0.0392^{***}	(0.0042)
Soldier Equippable	0.1775^{***}	(0.0037)
Sniper Equippable	0.0674^{***}	(0.0043)
Demoman Equippable	-0.0869^{***}	(0.0039)
Medic Equippable	0.0983^{***}	(0.0043)
Pyro Equippable	0.0663^{***}	(0.0038)
Heavy Equippable	-0.0318^{***}	(0.0039)
Scout Equippable	0.2527^{***}	(0.0039)
Widely Held Item (>3% of Active Players)	-1.5229^{***}	(0.0033)
With Week Time Dummies	X	
Observations	734,066	
R^2	0.7449	
Adjusted R^2	0.7449	
Residual Std. Error	$1.093 (\text{df} = 733853)$	
F Statistic	$1.88\text{e}+04^{***} \ (\text{df} = 114; 733853 \ )$	

Note: Standard errors in parentheses, and *p<0.1; **p<0.05; ***p<0.01

existed on or before September 20th 2010, when TF2 trading was introduced, were redesignated as vintage. Unusual quality items tend to attract the highest premium, a full 43000% premium above uniques. All unusual quality items possess some kind of visual effect, like flames, orbiting planets, or stinky-smelly lines. Unusual items are particularly rare, as they only appear with a very small probability from opening a crate and cannot come from any other source, and it is this rarity which is likely the reason which they command prices much higher than those of non-unusual items. Strange items, which will track in-game statistics, tend to exhibit a 571% premium above uniques. Quality "other" appears to attract the highest premium, however, items of this quality only appeared due to extremely unusual circumstances, akin to very rare coins minted with imperfections which make them very valuable to dedicated coin collectors but unavailable and inconsequential to everyone else, and accounting for only a negligible fraction of all coins. And, like coins, it is likely that some owners of the oddities are not even aware of the item's value. Thus we tend to see an extremely small number of transactions involving items of quality "other", but those transactions indicate that they are worth a small fortune. These, however, are not very representative of the broader economy.

All tools, weapons, and cosmetic items may be used by only one, some, or all character classes. Unlike quality or item type, this is non-exclusive designation. Character classes vary in speed, strength, and other abilities. For example medics are able heal teammates, and heavies are slow but may inflict and withstand a lot of damage. The highest equipability premiums come from items that can be carried by scouts and spies. Should an item be equipable by a scout, for example, it will tend to garner a 29% premium relative to a similar item that is not equipable by the scout.

Items that are held by a relatively large percentage of active players, defined as items that appear in more than 3% of active player inventories, tend to exhibit a large discount, trading for 78% lower than items that are not so widely held. To ensure this characteristic is time unvarying, the percentage holding statistic is taken on average over the whole sample. This is included in the regression to account for the potential price implication of an item's relative scarcity.

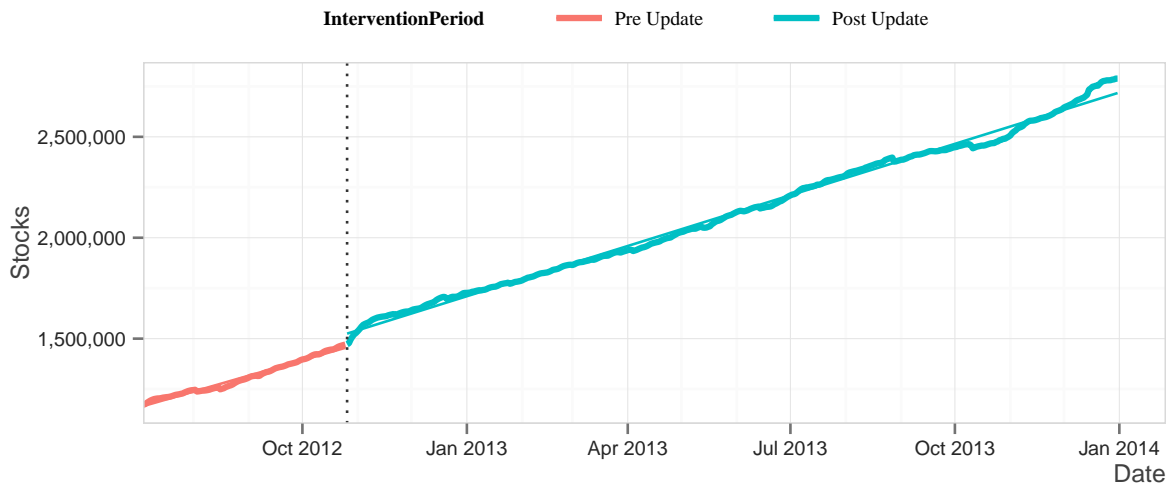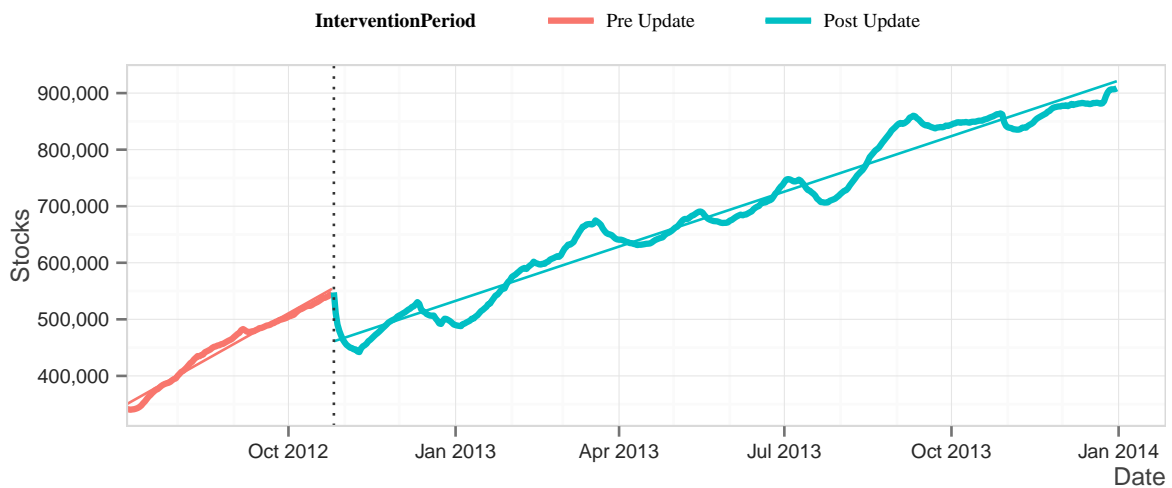Figure 15: Regression discontinuity on Refined Metal stocks

Figure 16: Regression discontinuity on Key stocks

D   Decline of the Aggregate Price Level

Figure 15 shows the outstanding item stocks of the primary currency metal, refined metals. Notice that right at the end of October, 2012, there is a sudden increase in the rate at which refined metals are entering into the economy. We argue that this is due to a major content update released on 26 October 2012. This date marks the point in time at which metals started their precipitous drop in value. This apparent positive supply shock appears to have been temporary, as the rate that metal stocks increase swiftly returns to a rate of increase only marginally higher than its rate prior to the event. But the fact that the rate of change of the stock of metals slowed did not correspond to a slowing rate of depreciation.

Figure 16 sheds some light on this question. Simultaneous with the sudden burst of metals that entered the economy, there was a sudden negative supply shock to our numeraire, keys. This corresponds to the major content update including new types of crates, leading to many more keys being consumed than purchased for a short period. The supply of metals suddenly increased and the supply of keys suddenly decreased; naturally, we would expect this to lead to an increase in the number of metals required to receive a key in exchange. The rate of increase of keys also appears to slow somewhat. This trend is confirmed by a regression discontinuity analysis using the following regression equation:

$$Stock_i = \beta_0 + \beta_1 DaysToPatch_i + \beta_2 PostPatch_i + \beta_3 Interaction_i + \varepsilon_i$$

Where $DaysToPatch$ is the number of days until the update went live, $PostPatch$ is a dummy variable that takes a value of zero on days which were prior to October 26 and a value of one after, and $Interaction$ is the product of these two variables. Our regression estimates are presented in Table 4. β_1 can be interpreted as the pre-update rate of expansion of the money supply for each currency and $\beta_1 + \beta_3$ is the post-update rate of expansion of that currency, thus β_3 is the difference in the trends before and after the cutoff.

Table 4 shows that the daily rate of increase in the stock of keys dropped from 1,810 to approximately 1,065, a 41% reduction. Simultaneously, the rate of change of metals increases slightly from 2,560 to 2,689, an 5% increase. This could explain the sudden and continuous depreciation;

Table 4: Before and After Halloween Time Trends for Keys (1) and Metals (2)

	Dependent variable:	
	Item Stocks	
	(1)	(2)
DaysToPatch	1,810***	2,560***
	(59)	(47)
PostPatch	−90,924***	78,012***
	(4,552)	(3,649)
Interaction	−745***	129***
	(60)	(48)
Constant	572,952***	1,457,520***
	(3,976)	(3,187)
Observations	500	500
R^2	0.977	0.998

Note: *p<0.1; **p<0.05; ***p<0.01

before October 26, keys were entering the economy at a rate that was not too far off of the rate that refined metals were entering, but after this event the rates at which the goods entered the economy differed drastically, leading to relative supplies drifting further and further away from each other.

The depreciation of metals can clearly be seen when comparing the nominal and real values of our representative basket. These are presented in Figures ?? and ??, respectively. The real value increases at an approximately constant rate as the average holdings of a representative agent increases over time, but the nominal value levels off and starts to decline right as the metal depreciation starts. This is due to the fact that the most commonly held items are generally metal-denominated and these items see shrinking key-values starting in October of 2012.