The Dynamics of Interacting Markets: First Results

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Abstract

The behavior of boundedly rational agents in two interacting markets is investigated. A discrete-time model of coupled financial and consumer markets is described. The integrated model is then used to investigate feedback effects between the coupled markets. In particular, the influence of the financial market on product development is demonstrated. The types of traders present in the financial market is shown to have a large effect on firm behavior and product development. In a financial market where traders favor particular products the firms are shown to develop these favored products instead of more profitable ones. The effect is quite strong despite the only feedback being through a noisy stock price, and despite the fact that only a third of share traders are directly influenced by product position.

1 Introduction

We investigate the behavior of boundedly rational agents in two interacting markets. The goal is to produce an integrated discrete-time model of financial and consumer markets. The global behavior of the model arises from the interaction of a large number of individual “agents”. The agents are designed to adapt over time, and model “boundedly rational” economic actors [Simon 1982]. That is, the agents are limited in their knowledge of the world and computational power.


The goal is to investigate the mutual influence of the two markets. In particular we can examine the influence of the financial market on production firm behavior. One might expect that it does not matter whether a firm bases its actions on its own estimate of performance, or on its stock price, as long as both are estimates of future profitability. This would no doubt be the case if firms and traders were fully rational. Both would have the same estimates of the value of a firm and its actions. However, when both are only boundedly rational, then their estimators might be in disagreement. In this case the financial market could have a positive or negative influence on firm performance.

In this paper we introduce the integrated model and make some initial observations on the interaction of the two markets. In the following sections we describe the implementation of the model. We then discuss the behavior of the production firms under different conditions in the financial market. We investigate the degree to which different financial traders can influence firm performance.
2 The Markets

The model consists of two markets: a consumer market and a financial equities market. The consumer market simulates the manufacture of a product by production firms, and the purchase of the product by consumers. The financial market simulates trading of shares. The shares are traded by financial traders. The two markets are coupled: The financial traders buy and sell shares in the production firms, and the firms are concerned with their share price. The traders can use the performance of a firm in the consumer market in order to make buy/hold/sell decisions. Similarly, the production firms can use positioning in product space to influence the decisions of financial traders (see figure 1).

The simulator runs in discrete time steps. Each step of the simulator consists of the following operations:

1. Production firms update their products or pricing policies based on performance in previous iterations.
2. Consumers make purchase decisions.
3. Firms receive an income based on their sales, and their position in product space.
4. Financial traders make buy/hold/sell decisions. Share prices are set and the market is cleared.

We describe the details of the markets, and how they interact, in the following sections.

3 The Consumer Market

The consumer market consists of firms which manufacture products, and consumers who purchase them. The product space is represented as a two-dimensional simplex. Each firm
can manufacture one product, represented by a point in this two-dimensional space. Consumers have fixed preferences about what product they would like to purchase. Consumer preferences are also represented in the two-dimensional product feature space. There is no distinction between product features and consumer perceptions of those features (see figure 2).

![Figure 2: The two-dimensional product space. Consumers have fixed product preferences (denoted by “*”). Firms can position their products (denoted by “o”) in the feature space.](image)

3.1 Firms

The production firms are adaptive learning agents. They adapt to consumer preferences and changing market conditions via a reinforcement learning algorithm [Sutton and Barto 1998]. In each iteration of the simulation the firms must examine market conditions and their own performance in the previous iteration, and then modify their product or pricing.

3.1.1 Reward Function

The firms adapt so as to maximize a reward signal received from the environment. The reward signal that we use is a combination of profitability relative to assets and change in share price relative to current share price. The reward received by firm $i$ at time $t$ is given by:

$$ r^i_t = \alpha_{as} \frac{as^i_t - as^i_{t-1}}{as^i_{t-1}} + \alpha_{sp} \frac{sp^i_t - sp^i_{t-1}}{sp^i_{t-1}} $$

(1)

where $as^i_t$ denotes the (cash) assets of firm $i$ at time $t$, and $sp^i_t$ denotes the share price of firm $i$ at time $t$. The constants $\alpha_{as}$ and $\alpha_{sp}$ are fixed at the beginning of the simulation and held constant throughout. They trade off the relative importance of profits and stock price in a firm’s decision-making process.

3.1.2 State Description

The firms do not have complete information about the environment in which they operate. In particular, they do not have direct access to consumer preferences. They must infer what the consumers want by observing what they purchase. Purchase information is summarized by performing “k-means” clustering on consumer purchases. The number of cluster centers is fixed at the start of the simulation. Each firm is given the positions of the cluster centers in feature space, along with some additional state information. The state information takes the
form of a bit-vector. of “features”. The information available to each firm in a given iteration is summarized in Table 1.

Table 1: Features Available to Production Firms.

<table>
<thead>
<tr>
<th>Feature</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Assets</td>
<td>1 if assets increased in the previous iteration, 0 otherwise</td>
</tr>
<tr>
<td>Share Price</td>
<td>1 if share price increased in the previous iteration, 0 otherwise</td>
</tr>
<tr>
<td>Mean Price</td>
<td>1 if product price is greater than mean price of competitors products, 0 otherwise</td>
</tr>
<tr>
<td>Cluster Center 1</td>
<td>A bit-vector that encodes the position of cluster center 1</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>Cluster Center N</td>
<td>A bit-vector that encodes the position of cluster center N</td>
</tr>
</tbody>
</table>

The cluster centers are encoded as binary vectors. Each cluster center can be described as a pair of numbers \((a, b) \in [0, 1] \times [0, 1] \). Two corresponding binary vectors are generated by “binning”. Each axis is divided into \(K\) bins. The bit representing the bin occupied by each number is set to 1. All other bits are 0. For example, given 10 bins per axis and a cluster center \((0.42, 0.61)\), the resulting bit vector is \((00001000000000010000)\) (see figure 3).

Figure 3: Computing the bit vector representation of a cluster center. In this case the cluster center is located at \((0.42, 0.61)\) and the resulting bit-vector is \((00001000000000010000)\).

3.1.3 Actions

In each iteration the firms can take one of several actions. The actions are summarized in Table 2. The “Do Nothing” and “Increase/Decrease price” actions are self-explanatory. The “Move product” actions move the features of the product produced by the firm a small distance in the direction of the chosen cluster center. For example, if the action selected by
Table 2: Actions Available to Production Firms.

<table>
<thead>
<tr>
<th>Action</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Do Nothing</td>
<td>Take no actions in this iteration.</td>
</tr>
<tr>
<td>Increase Price</td>
<td>Increase the product price by 1.</td>
</tr>
<tr>
<td>Decrease Price</td>
<td>Decrease the product price by 1.</td>
</tr>
<tr>
<td>Move Towards Center 1</td>
<td>Move the product features towards cluster center 1.</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>Move Towards Center N</td>
<td>Move the product features towards cluster center N.</td>
</tr>
</tbody>
</table>

firm \(i\) is “Move Towards Center \(j\)” then the product is modified as follows:

\[
p_{ik}^{t+1} \leftarrow p_{ik}^t + \nu (c_{jk}^i - p_{ik}^t) \tag{2}
\]

where \(k \in \{1, 2\}\) enumerates product features, and \(c_{jk}^i\) is the \(k\)th feature value of cluster center \(j\). The update rate \(\nu \in (0, 1]\) is a small fixed constant.

Some actions have costs. In particular, when a firm repositions its product, it incurs a small fixed cost for each move. There is also a feature-dependent manufacturing cost for each unit of the product produced. All firms share a cost vector \(c\), which is initialized at the beginning of the simulation. The cost of manufacturing a unit of product \(p\) with features \(p\) is given by:

\[
\text{cost}(p) = c^\top p \tag{3}
\]

3.1.4 Value Function

Given a bit vector representing the current state of the simulator, a production firm makes strategic decisions based on its value function. Value functions (sometimes called “cost-to-go” functions in the control theory literature) are a basic component of reinforcement learning and optimal control theory [Bertsekas and Tsitsiklis 1996; Sutton and Barto 1998]. Given some “reward signal” \(r\) at each time step, the learning agent attempts to act so as to maximize the total (discounted) reward, or expected return, received over the course of the task:

\[
R_t = \left\langle \sum_{\tau=t}^{\infty} \gamma^{\tau-t} r_\tau \right\rangle_\pi \tag{4}
\]

Here \(\langle \cdot \rangle\) denotes taking expectations and \(\pi\) is the policy of the firm. The policy is a (possibly stochastic) mapping from the current state to an action: \(\pi : S \to \Delta^{|A|}\). In our case \(S\) is the set of possible (bit vector) state descriptions, and \(A\) is the set of possible actions taken by a firm. The range \(\Delta^{|A|}\) is the set of probability distributions over actions in \(A\). Note that the discount factor \(\gamma\) can be reasonably related to the rate of inflation or the interest rate in economic simulations.
Given the above definitions, the action-value function is defined as the expected return conditioned on the current state and action:

\[ Q^\pi(s, a) = \langle \sum_{\tau=t}^{\infty} \gamma^{\tau-t} r_\tau | s_t = s, a_t = a \rangle \pi \]  

The value function summarizes how much reward the learner should expect to receive over the course of the task if it executes a given action in the current state, and then follows policy \( \pi \).

Since the state space is quite large, we use a parameterized function approximator to approximate the value function. For the production firms, the value function approximator is a linear function of the state bit vector:

\[ \hat{Q}^\pi(s, a; \theta) = \sum_i \theta_i a_i s_i = \theta_a \top s \]  

### 3.1.5 Reinforcement Learning

We use a reinforcement learning technique called SARSA [Rummery and Niranjan 1994; Sutton 1996]. An approximation to the value function is iteratively refined during the course of the task:

\[ \theta \leftarrow \theta + \lambda \left( r_t + \gamma \hat{Q}^\pi(s_{t+1}, a_{t+1}; \theta) - \hat{Q}^\pi(s_t, a_t; \theta) \right) \frac{\partial \hat{Q}^\pi}{\partial \theta} \bigg|_{s_t, a_t} \]  

where \( \lambda \) is a small learning rate. Intuitively this learning rule minimizes the squared error between the approximate value function and a bootstrap estimate based on the current reward and the future value function. Theoretically, this technique has been closely linked to dynamic programming and Monte Carlo approximation techniques [Sutton and Barto 1998].

After each value function update, the policy is updated by being greedy with respect to the value function:

\[ \pi(s) \leftarrow \arg\max_a \hat{Q}^\pi(s, a) \]  

The theoretical convergence properties of SARSA assume a stationary stochastic environment. When there is more than one adaptive firm in the environment, this assumption is incorrect. However, it has been shown that reinforcement learning can be used to approximately solve arbitrary-sum competitive games [Tesauro 1999]. Also, the method assumes that the state is fully visible. The state vector is assumed to contain all of the information necessary to make an optimal decision. In other words we are assuming that the firm is solving a fully-observable Markov decision process (MDP). This assumption is clearly false, since the state vector does not include necessary information such as consumer preferences. Fully observable reinforcement learning algorithms have been used previously to (approximately) solve partially observable problems [Jaakkola, Singh, and Jordan 1995]. This approximation can be seen as one source of “boundedness” in a boundedly rational firm.

### 3.2 Consumers

Consumers are defined by their product preference. Each consumer agent is initialized with a random preference in product feature space. During each iteration of the simulation, a consumer must make a product purchase decision. For each available product, the consumer
computes a measure of “dissatisfaction” with the product. Dissatisfaction is a function of product price and the distance between the product and the consumer’s preferred product. Consumer $c$’s dissatisfaction with product $p$ is given by:

$$\text{DIS}_{c,p} = \alpha \frac{D(p_c, p)}{\max_{p'} D(p_c, p')} + (1 - \alpha)\frac{P(p)}{\max_{p'} P(p')} \quad (9)$$

where $P(p)$ denotes the price of product $p$, and $\alpha$ trades off the importance of product features and price. The measure $D(p, q)$ is the Euclidean distance in feature space between products $p$ and $q$:

$$D(p, q) = (p - q)^\top W (p - q)$$

Here bold-faced letters denote the feature-vector representations of products. The diagonal matrix $W$ is common to all consumers and models the relative importance of features in the feature space.

Every consumer is also initialized with a different “ceiling” price $P_{c,max}$. If all product prices are above its ceiling, a consumer will simply make no purchase in that iteration. Given dissatisfaction ratings for all products, and given the set of products with prices below the ceiling in iteration $t$, consumer $c$ buys the product $p_{ct}$ from this set with the lowest dissatisfaction rating:

$$p_{ct} = \arg\min_p \{\text{DIS}_{c,p}\} : p \in \{q : P(q) < P_{c,max}\} \quad (11)$$

### 4 The Financial Market

We use a financial market closely modeled on that of Steiglitz, Honig, and Cohen [1995]. The financial market simulates the buying and selling of shares in the production firms. The market is composed of financial trading agents and a central market clearance mechanism. In each iteration of the simulator, the financial agents make buy/hold/sell decisions and post their orders to the market. The central clearance mechanism sets a price and matches buyers and sellers. Each iteration of the financial market simulator consists of the following steps:

1. Each financial traders makes a buy/hold/sell decision. It must select a bid/ask price and sets the volume of shares. If buying, it tries to spend a fraction $P_m$ of its funds. If selling, it tries to sell a fraction $P_s$ of its holdings.

2. The transaction requests are collected by the clearance mechanism. The supply and demand curves for the market are constructed, and a price is selected that maximizes the volume of shares traded.

3. Buyers and sellers are randomly ordered, and transactions are carried out in this order until as many shares have been traded as possible.

#### 4.1 The Market Clearance Mechanism

We use a sealed-bid auction, where the clearance mechanism chooses the price at which trading volume is maximized. The first step is to construct supply and demand curves based
Figure 4: Supply and demand curves. Supply is marked with “O” and increases with price. Demand, marked with “*” decreases with price. The market price (vertical line) is set to a price which maximizes the volume traded. In this case, the market price is 4.3.

Note that there is a range of prices that would maximize volume. We select the maximum price in this range. If there are buy orders but no sellers then the share price is set to the maximum bid. If there are only sell orders then the price is set to the minimum price asked. If there are no orders in a time period, then the price remains unchanged.

The financial market is occupied by a heterogenous mixture of traders. All of the traders operate by trying to predict price movements. We describe the different trader types in the following sections. Each trader specializes in a single firm, and only buys or sells shares in this firm. Each trader is initialized with a supply of cash, and an initial supply of shares in its firm of interest.

4.2 Fundamentalists

The fundamentalist traders build on the work of [Gaunersdorfer 2000]. Fundamentalist traders base share price on the economic performance of the firm in the consumer market. Fundamentalists try to compute the “fundamental price” of a stock. Given knowledge of the dividend paid by a firm \( y_t \), the fundamental price would be:

\[
p^*_t = \sum_{t=1}^{\infty} \frac{y_t}{R_I}
\]

where \( R_I \) is the risk-free growth rate. Unfortunately, the traders do not know what the profitability of a firm will be in advance. Instead they use a myopic one-step-ahead predictor:
They assume that all future dividends will be equal to the current dividend. Given this assumption the predicted fundamental price is $\hat{p}_t = y_t / (R_t - 1)$.

Fundamentalist traders assume that a share price will move towards the fundamental price:

$$p_{t+1}^e = p_t + \nu_t (\hat{p}_t - p_t)$$

where $\nu_t \in [0, 1]$ is a learning rate. The trader makes a buy/sell decision using the following rule:

$$\text{decision} = \begin{cases} 
\text{buy} & \text{if } p_t < p_{t+1}^e(1 - \text{margin}) \\
\text{sell} & \text{if } p_t > p_{t+1}^e(1 + \text{margin}) \\
\text{hold} & \text{otherwise}
\end{cases}$$

where “margin” is a fixed profit margin. The profit margin is selected for each firm separately. It is randomly chosen from a uniform distribution on $[0, 0.1]$. If the fundamentalist decides to buy, it offers a price of $p_t(1 + \text{margin})$. If it decides to sell, it asks a price of $p_t(1 - \text{margin})$ (i.e., slightly above or below the current price respectively). The use of the same margin for both purchase decisions and to construct a price is not necessary, and it just done for convenience.

### 4.3 Chartists

Chartists try to follow trends in the market. They also base their trading decisions on the predicted price of their stock of interest. However, instead of using a predictor based on a firm’s performance in the consumer market, they assume that any trend in the market will continue. For the Chartist, the prediction of future price is given by:

$$p_{t+1}^e = p_t + \nu (p_t - p_{t-1})$$

where $\nu \in [0, 1]$. Except for this difference, Chartists behave the same as Fundamentalists. They base their buy/hold/sell decisions on Eq.(14). They also have fixed, pre-specified profit margins, and construct an offered/desired price in the same way.

### 4.4 Hypists

Previous work on financial market models has focused on fundamentalist and chartist traders. We are interested in the effects of the financial market on product development. In order to study the degree to which firms can be influenced by the financial market we introduce a new type of trader.

Hypists are meant to simulate traders who base their trading decisions on what they think will be “the next big thing”. Like the other traders, Hypists base their buying and selling decisions on predicted price movements. However, the Hypist bases its buying decision solely on the position of the firm’s product in product space (see figure 5).

Like the consumers, Hypists are initialized with a fixed preferred point in product space. If a firm moves its product closer to this preferred point, the Hypist assumes that the stock price will increase. Otherwise, the Hypist assumes that the stock price will decrease. The distance is just measured as Euclidean distance in product feature space. If the price is predicted to increase in the future, it tries to buy, and bids $p_t(1 + \text{margin})$. Otherwise, it tries to sell with an offer of $p_t(1 - \text{margin})$. 


Figure 5: Hypist decision making. If the product moves closer to the Hypist’s preferred product, it will buy. If it moves away, it will sell.

One might ask if this is a realistic model of the way some financial traders behave. We would argue that the recent “dot-com” phenomenon demonstrates exactly this kind of effect. For example, [Subramani and Walden 2001] have shown evidence for positive cumulative abnormal returns to shareholders following immediately after “e-commerce” announcements by publicly-traded firms during the period October 1, 1998 to December 31, 1998.

4.5 Market Liquidity and Randomness

When the financial market includes only the traders mentioned above, there is a lack of randomness in the market. Much of the time all agents agree on what will happen in the market. During these times, trading volume drops to very low levels and prices become static.

In order to introduce randomness and increase trading volume, we give each trader a “randomness threshold” $T_r$. This is the probability that in a given iteration the agent will make a random buy/sell decision instead of basing its decision on predicted price movement. A randomly-acting agent will buy or sell with probability 0.5. When buying the agent tries to spend a fraction $P_{m}$ of its funds. When selling, the agent will try to sell a fraction $P_{s}$ of its holdings. Randomly acting agents ask or offer a price of $p_t + \eta$, where $\eta \in \mathcal{N}(0, \sigma^2)$ is a random number drawn from a zero-mean Normal distribution with standard deviation $\sigma$.

5 Simulation Results

There are a number of parameter values which must be decided before a simulation can be run. We have not done extensive tests on the sensitivity of the simulator to different parameter regimes. Initial experiments indicate that financial market parameters such as $P_{m}$, $P_{s}$ and $T_r$ can have a large effect on the liquidity of the financial market. Otherwise, the simulator seems to be relatively insensitive to parameter values. We held the parameter
values fixed for all of the following simulation runs. The parameters and their values are summarized in 3.

Table 3: Parameter values for the Combined Markets Simulator

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Range</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha_{as}$</td>
<td>strength of profitability reinforcement</td>
<td>[0, 1]</td>
<td>1.0</td>
</tr>
<tr>
<td>$\alpha_{sp}$</td>
<td>strength of stock price reinforcement</td>
<td>[0, 1]</td>
<td>1.0</td>
</tr>
<tr>
<td>N</td>
<td>Number of cluster centers</td>
<td>N</td>
<td>3</td>
</tr>
<tr>
<td>K</td>
<td>Number of bins</td>
<td>N</td>
<td>10</td>
</tr>
<tr>
<td>$\nu$</td>
<td>product update learning rate</td>
<td>[0, 1]</td>
<td>0.001</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>Reinforcement Learning discount factor</td>
<td>[0, 1]</td>
<td>0.95</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>Consumer feature/price tradeoff</td>
<td>[0, 1]</td>
<td>0.5</td>
</tr>
<tr>
<td>$P_{m}$</td>
<td>Fraction of trader funds used for buying</td>
<td>[0, 1]</td>
<td>0.2</td>
</tr>
<tr>
<td>$P_{s}$</td>
<td>Fraction of trader shares used for selling</td>
<td>[0, 1]</td>
<td>0.2</td>
</tr>
<tr>
<td>$T_{r}$</td>
<td>Trader randomness threshold</td>
<td>[0, 1]</td>
<td>0.2</td>
</tr>
<tr>
<td>$\nu_{t}$</td>
<td>Trader price update rate</td>
<td>[0, 1]</td>
<td>1.0</td>
</tr>
<tr>
<td>margin</td>
<td>Trader profitability margin</td>
<td>[0, 1]</td>
<td>uniform in [0, 0.1]</td>
</tr>
</tbody>
</table>

5.1 Financial Market Influence on Product Development

To investigate feedback effects between the financial and consumer market, we ran three sets of simulation. In the first set the production firms ignored their stock price when making decisions ($\alpha_{sp} = 0$). In the second, the financial market did influence reward ($\alpha_{sp} = \alpha_{as} = 1.0$), but there were no hypist traders in the market. In the third set of simulations, $\alpha_{sp} = \alpha_{as} = 1.0$, and there were hypists in the market. Each set of simulations consisted of twenty repetitions with different random initializations of consumer and hypist preferences.

Each repetition contained 2 firms, 50 traders and 200 consumers. When hypists were present, hypist product preferences were Gaussian distributed around a mean value of [0.1 0.9]. Figure 6 shows the mean profits of the firms in the last 5000 iterations of the simulation, averaged over the 2 firms and 20 runs. Figure 6(a) shows performance with no financial market influence, figure 6(b) shows performance without hypists in the financial market, and figure 6(c) shows performance with hypists. The mean profitability with no market influence was 2459.8. With no hypists in the marketplace it fell to 1861.7. With hypists in the marketplace, the mean profitability dropped further to 1461.9. Both drops are statistically significant (estimated P-values $\approx 0$ and $10^{-271}$ respectively, estimated with a Wilcoxon signed rank test).

We can confirm that product placement is affected by hypists by examining product movement decisions made during the simulations. We computed the angle between the actual direction of product movement, and the movement direction that would have been preferred by hypists. Without hypists the mean angle is 90.8. With hypists it is 87.5. This difference is significant (estimated P-value $1.5 \times 10^{-4}$, estimated with a Wilcoxon signed rank test).

Figures 7(a) and (b) show the placement of products in the last 2000 iterations of the simulation. Large circles indicate clusters of consumer preferences. The small circle at [0.1 0.9] shows the mean hypist product preference.
The product movement histograms show this effect more clearly. Figures 7 (c) and (d) are histograms showing the angle between the direction that a product has moved from its original location, and the direction it would have moved to satisfy the hypists’ preferences. Smaller angles indicate greater agreement with hypist preferences. In a market with hypists, product movement is in significantly greater agreement with hypists’ preferences (estimated P-value $1.5 \times 10^{-4}$, estimated with a Wilcoxon signed rank test). (see figure 8 for an explanation of how product movement is computed).

We can see from the figures that when Hypists are present in the market, they do not dominate product placement. The firms still try to select products that are profitable in the consumer market. However, notice that many more products in figure 7(b) are located right on top of the Hypists’ optimal product. This area of product space is empty in figure 7(a).

So far we have seen that the preferences of the financial traders can influence product development. Implicitly this shows that a firm’s performance and product positioning can influence its stock price, since stock price is the only feedback mechanism that could influence product placement. We can also look explicitly at the stock price as a function of having
or not having hypists in the marketplace.

Figure 9 shows the share price of the two firms, averaged across firm and averaged across the 20 trials. First notice that the average stock price rises in all cases. This is consistent with the fact that average profitability rises over the course of the simulation. When there is no market influence, profits are higher, and stock price is similarly higher. More interesting is that when hypists are present in the market, the stock price rises much faster than in either of the other two cases. This is what we would expect to see: The influence of the market on product positioning requires that the hypists have an influence on the share price.

6 Conclusions

We have described an integrated model of financial and consumer markets. The model builds on previous work by simplifying and integrating consumer and financial market
Figure 8: How product movement is computed. The movement vector for the product was compared to the movement direction that would have most satisfied the hypists. The histograms in Figures 7 (c) and (d) show the angle between these two vectors. Smaller angle means better agreement with hypist preferences.

Figure 9: Average stock price with no market influence, and with and without hypists. In general, the market value of firms rises over the course of the simulation. However, the rate of growth in firm value is dramatically greater when hypists are present in the financial market.
models. We have shown that the interaction of the two markets can contain interesting dynamics. Initial results show that the financial market can have an influence on production firm performance. The degree of the effect is dependent on the types of traders present in the financial market. This feedback effect can be surprisingly strong, considering the indirect route by which the information is transmitted. In particular, the influence of hypists is interesting considering that they constitute only a fraction of traders, and that the share price signal for individual firms is very noisy. The hypists have a strong influence on the stock market, and through share price also have a strong influence on product development.

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