Effect of Social Networks on Consumers' Inclination towards Online Shopping using Transaction Cost Analysis in an Agent-based Framework

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Abstract. **The increasing popularity of on-line social networks has redefined the way people interact. As a consequence, consumers now exchange opinions about their purchasing behavior on social networking websites, which subsequently influences their shopping decision. One of the fundamental reasons for the evolution of an economic system is the alteration of consumer choice over time. In this paper, we study the all-pervading influence of social networks on consumers' inclination towards on-line shopping, which in turn affects the very functioning of certain traditional ("brick-and-mortar") markets. More specifically, we study a model of influence in social networks to show the change in consumer behavior patterns using an agent based interaction model. Agent-based modeling and simulation (ABMS) is a new approach to modeling systems that comprise interacting autonomous agents. It is a promising tool for modeling social life as interactions among adaptive agents who influence one another in response to the influences they themselves receive. Building upon the Transaction Cost Economics theory, the objective of our study is to examine the effect of social networks on the "perceived transaction cost" of an individual, which is what determines his/her inclination to buy online. Using agent-based models, we create a virtual population including several hundreds of artificial consumers to study the rate of adoption of on-line shopping by consumers. In conventional modeling of the diffusion process, there is no way to describe how the cognitive aspects of agents as well as diversity of the agents' decision making processes give rise to the observed rate, extent or order of the diffusion process. A particular issue explicitly examined in our model is how customers interact with early adopters of on-line shopping and modify their perceived transaction cost in deciding to buy on-line. We model the adoption decision of individuals as a gradual transformation affected by three factors: (1) the number of early adopters (influencers), (2) the average numbers of direct friends of the adopters and potential adopters, and (3) the type of commodity/market under consideration.**

Keywords- Transaction Cost, Social Network, Agent based modeling and Simulation, on-line shopping, Consumer Behavior Modeling

I. INTRODUCTION

With the gradual expansion of the internet and World Wide Web, online shopping has progressively been gaining primacy throughout the world, drastically altering the established structure of markets that were known till its advent [1, 2]. E-commerce, the online shopping system, has brought down political and physical barriers giving everyone in the world an equal playing ground for their market. However, the mushrooming of online stores and retailers over the past decade has had far-reaching consequences for the traditional system.

The gradual ascent of these stores via changing consumer perceptions is taking a toll on conventional markets. The recent bankruptcy of Borders chain of bookstores [3], shutdown of the India-based bookstore Manney's, the closure of electronic retail stores CompUSA and Circuit City, the near-bankruptcy of Best Buy (which has witnessed a 40% drop in market shares in 2011 itself), and the gradual displacement of small-time travel agents to make way for their online counterparts, are some glaring examples that point in this direction. Amazon, arguably one of the most successful online firms, is currently valued at over $79 billion, which is 40 percent higher than the combined value of two large and successful offline retailers, Target and Kohl's, who have 2800 stores between them. Barnes & Noble, while still large, has also seen its market share diminish markedly [4].

E-commerce technology can affect both demand and supply fundamentals of markets [4]. On the demand side, e-commerce precludes potential customers from inspecting goods prior to purchase. Further, online sellers tend to be newer firms and may have less brand or reputation capital to signal or bond quality. These factors can create information asymmetries between buyers and sellers, which does not arise for offline purchases. Online sales also often involve a delay between purchase and consumption, owing to the lapse of time between placing an order and having the product physically delivered. At the same time, however, e-commerce technologies reduce consumer search costs, making it easier to (virtually) compare different producers' products and prices. On the supply side, e-commerce enables new distribution technologies that can reduce supply chain costs and improve service [4, 5, 6].

Consumers interact through processes such as imitation and conditioning, by means of individuals and groups of individuals (friends, family, etc.), which comprise the "social contacts" of the consumer [7, 8]. These contacts, according to their cohesion degree, influence more or less the consumer's decisions. The online social network [9], which is a direct consequence of the same technological boom of the 90s that brought about the dominance of e-commerce, has revolutionized the way consumers interact with and influence each other. Costs of transmitting and receiving information have dramatically been reduced, thus encouraging them to exchange their opinions about product usability on electronic bulletin boards or social networking services (SNS), with their social contacts [10]. These interactions tend to change the "*transaction cost*" individuals associate with online shopping. A transaction cost is a cost incurred in making an economic exchange, i.e, it is the cost of participating in a market [11]. Transaction cost economics (TCE) is most commonly associated with the work of Oliver Williamson [12, 13]. Using this transaction cost economics perspective, Teo, et al.[14] have presented an empirical study for understanding consumers' on-line buying behavior. The results indicate that **consumers' willingness to buy online is negatively associated with their perceived transaction cost.**

In this paper, our objective is to show how a consumer who is a proponent of online shopping (we call him/her the "***influencer***") influences the perceived transaction cost of another consumer (we call him/her the "***influencee***") and, in turn, how an "***influencee***" eventually adopts the shopping behavior of the "***influencer***". In this context, we study how the social network accelerates this adoption process by constantly altering the transaction costs attached with online shopping, as perceived by individuals. This changing perception propagates it further, and the "early adopters" (of online shopping) soon influence the population to bring an "early majority" into being [15]. The transition between these two is covered in a considerably shorter period of time than it would have been in the absence of the social network.

To study these effects, agent-based simulation model is an invaluable tool [16]. Agent-based modeling is a bottom-up approach to understanding and analyzing complex, non-linear markets [17]. The method involves creating artificial agents designed to mimic the attributes and behaviors of their real-world counterparts. Using such a model, we may incorporate factors of social influence, heterogeneity, erratic rationality and in general present a fairly realistic picture of the consequences of inter-agent interaction [18].

Using agent-based models, we create a virtual population consisting of several hundreds of artificial consumers to study the rate of adoption of on-line shopping by consumers. A particular issue explicitly examined in our model is how consumers interact with "early adopters" (the "***influencers***", as discussed earlier) and modify the perceived transaction cost of the **"influencees"**, eventually encouraging them to buy on-line. We model the adoption decision of individuals as a gradual transformation affected by three factors: (1) the number of early adopters (influencers), (2) the average numbers of direct friends of the early adopters and potential adopters, and (3) the type of commodity under consideration.

II. TRANSACTION COST BASED CONSUMER MODEL

Transaction cost economics (TCE) theoretically explains why a transaction subject favors a particular form of transaction over others. The basic principle of TCE is that people like to conduct transactions in the most economic way. Since purchasing from online stores can be considered a choice between the internet and traditional stores, it is reasonable to assume that consumers will go with the channel that has the lower transaction cost [19]. Therefore, TCE becomes a viable theory for explaining the internet shopping decision of consumers. Specifically, whether a consumer would buy a product through the Internet is determined by the perceived transaction cost of the consumer [14].

In order to study how an ***influencer*** influences the perceived transaction cost of an ***influencee*** in favour of online shopping and, in turn, how the influencee eventually adopts the influencer's shopping behavior, we define below a set of components of overall transaction cost as perceived by a consumer.

A. Components of Transaction Cost

Based on literature survey, we have postulated the following components of Transaction Cost for our analysis and consumers' initial perception of transaction cost with respect to online vis-à-vis offline purchase [14]:

- **Product Uncertainty** – Uncertainty refers to the cost associated with unexpected outcome and asymmetry of information [12, 13]. Therefore, a higher level of uncertainty generally implies a higher transaction cost because both parties in the transaction will spend more time and effort in monitoring the transaction process. The performance uncertainty of products bought through online shopping is one of the consumers' major concerns [14]. Thus, consumers' initial perception about high product uncertainty in on-line shopping increases perceived transaction cost.
- **Trust** – Trust has been incorporated into the TCE literature by many researchers [20]. Trust can be hypothesized to be a variable that is likely to reduce transaction costs. In e-commerce, online stores depend on an electronic storefront to act on their behalf and there are fewer assurances for consumers that the online store will stay in business for some time. Moreover, consumers have to rely on online stores to perform many activities in the transaction process such as examining product quality and providing after-sale services. Therefore, online

retailers face a situation in which consumers' initial perception about trust might be expected to be inherently negative [14].

- **Convenience** –We define convenience as the advantages (i.e., saving time and effort, 24x7 shopping) that buyers enjoy through online buying [21]. Online buying, as an alternative to physical shopping, offers more convenience to consumers because they can save time and effort in searching for product information. In addition, consumers can also buy products from online stores at any time. Therefore, consumers usually perceive that convenience is high in on-line shopping.

- **Economic utility** –Economic utility refers to the capability of online stores to provide comparison-shopping for competitive prices and bargains. Also, lower cost is one of the principle reasons why consumers buy online [14]. Therefore, consumers usually perceive economic utility to be high in on-line shopping, in turn lowering the perceived transaction cost in this respect.

Now, let the Perceived Transaction Cost associated with :

- Product Uncertainty be T_P such that increase in Product Uncertainty will increase T_P
- Trust be T_T such that increase in Trust will decrease T_T
- Convenience be T_C such that increase in Convenience will decrease T_C
- Economic utility be T_E such that increase in Economic Utility will decrease T_E

The total transaction cost perceived by any consumer is a weighted summation of these four components, as given below:

$$T_{TOTAL} = W_p * T_P + W_t * T_T + W_c * T_C + W_e * T_E,$$

where, the weight associated with each component indicates the consumer's priority towards that component.

For example, let us assume that two consumers X and Y feel (i) quality of products procured through on-line shopping are highly uncertain; (ii) on-line shops are not at all trustworthy; (iii) however, on-line shopping is convenient; and, (iv) the products are cheaper at on-line shops. In a ten-point scale, let us assume that X and Y associate the following transaction costs against each of its components: (i) $T_P = 9$; (ii) $T_T = 9$; (iii) $T_C = 2$; and, (iv) $T_E = 1$. However, let us assume that the priority / preference of X and Y are different. X gives more weightage to product uncertainty and trustworthiness, whereas Y gives more weightage to convenience and economic utility.

So, for X, $W_p^x = 0.4$; $W_t^x = 0.4$; $W_c^x = 0.1$ and $W_e^x = 0.1$. Whereas, for Y, $W_p^y = 0.1$; $W_t^y = 0.1$; $W_c^y = 0.4$ and $W_e^y = 0.4$.

So, T_{TOTAL} (for X) = 3.6 + 3.6 + .2 + .2 = 7.6;
and, T_{TOTAL} (for Y) = 0.9+ 0.9+ 0.8 + 0.8 = 3.6

Therefore, even if the components of perceived transaction costs of X and Y are same, the total transaction cost will be different depending on their priorities and preferences.

It is to be noted that we consider T_{TOTAL} of an individual to be determined solely by the interaction of the four mutually exclusive components (T_P , T_T ,T_C and T_E) defined above. Also, weights are intrinsic to a consumer and cannot be influenced by other consumers; only his/her perception about T_P , T_T ,T_C and T_E can be influenced

B. Assumptions

- The consumers share some social network platform (e.g. Facebook) and as stated earlier, we classify the consumers into two categories: the ***influencer*** and the ***influencee***.
- Our model focuses on only that section of the world population which has a workable knowledge of the computer, and actively participates in social networking (e.g.Facebook).
- We exclude items of daily use such as groceries, medicines, and any other good that has a fairly inelastic demand from our analysis. Even in an increasingly network-dependent shopping scenario, these items can never be completely free from brick-and-mortar establishments.
- We assume that we can measure the values of T_P , T_T ,T_C and T_E for each consumer on a 10-point scale, and estimate the relative weights each consumer assigns to each factor respectively.
- The *influencer* influences his social circle at some time period, decreasing gradually the perceived transaction costs of each of his *influence-contacts*. Two *influencers* cannot alter their transaction costs upon interaction (even though one might have a relatively lower T_{TOTAL}).
- An *influencee* becomes an *influencer,* once her/his perceived transaction cost falls below a certain threshold value T^H. Beyond this, influence ceases to be exerted.
- The transaction costs associated with the *influencers* remain invariant at all times. We ignore all such interactions of the influencer (e.g with the online stores or other influencers) and all such situations that might arise as a result of certain exogenous factors, which might lead to a change in her/his own perceived transaction cost, whether upward or downward. Our *influencers* are, in that sense, "static."
- We do not take into account the relative differences in influencing power of the influencers, as also the relative "stubbornness" of the *influencees*.

C. Process of Influence and Adoption

Let us take an example scenario. Let us assume that consumer X is a proponent of online shopping. From his/her experience, X is well-aware of the facilities offered by popular on-line shopping sites (e.g. "payment on delivery" to ***increase trust***, good customer service and replacement of defective products promptly at the cost of vendors to ***reduce product uncertainty***, offering huge discounts and comparison-shopping to ***improve economic utility*** and an easy-to-interact on-line interface to provide a smooth shopping experience, thus ***improving convenience***). Accordingly, being in favor of on-line shopping, X associates a low transaction cost with each component. Let us assume that X assigns the following values of transaction costs on a ten-point scale as: $T_P = 3$, $T_T = 1$,$T_C = 2$ and $T_E = 2$. During his/her course of interaction in the social network, X interacts with his/her friend Y who is a conventional brick-and-mortar shopper and is skeptical about on-line shopping. Being ***not*** in favor of on-line shopping, Y associates a moderate to high transaction cost with each component. Let us assume that Y assigns the following values of transaction costs on a ten-point scale as: $T_P = 8$, $T_T = 9$,$T_C = 5$ and $T_E = 4$. Now, in course of interaction, Y becomes more aware about on-line shopping and slowly appreciates the product-specific benefits of on-line shopping vis-à-vis brick-and-mortar shopping. Y gradually adopts the shopping behavior of X. Thus, X acts as an ***influencer*** who gradually reduces the perceived transaction cost of Y (the ***influencee***) with respect to on-line shopping. The process of influence in our model is illustrated below.

The adoption process is initiated when an *influencer* interacts with his/her friends within his/her social network framework. This process of interaction will influence an *influencee* (provided s/he is a friend of the influencer) to alter the transaction cost s/he associates with T_P, T_T, T_C and T_E respectively. Let us assume that X is an influencer interacting with an influencee Y. Let

$T_P^X = T_P$ of X (Transaction cost for Product Uncertainty)

$T_T^X = T_T$ of X (Transaction cost for Trust)

$T_C^X = T_C$ of X (Transaction cost for Convenience)

$T_E^X = T_E$ of X (Transaction cost for Economic Utility)

Similarly, $T_P^Y = T_P$ of influencee Y

$T_T^Y = T_T$ of influencee Y

$T_C^Y = T_C$ of influencee Y

$T_E^Y = T_E$ of influencee Y.

And, S = commodity factor, $0<S<1$,

where, S depends on the nature of the commodity we consider e.g. shoes/ apparel / books / air-ticketing etc. S is closer to 1 when the commodity does not require any look-and-feel type inspection and service is guaranteed (e.g. book, air-ticket, etc). S is closer to 0, when the commodity requires a look-and-feel type inspection and service is uncertain (e.g. shoes, apparel, etc.)

After influence, each component of the *influencee's* transaction cost will be reduced as follows:

$$T_P^{Y(after)} = T_P^Y - S*T_P^X$$
$$T_T^{Y(after)} = T_T^Y - S*T_P^X$$
$$T_C^{Y(after)} = T_C^Y - S*T_P^X$$
$$T_E^{Y(after)} = T_E^Y - S*T_P^X$$

So, when S is closer to 1, transaction costs of the *influencee* will reduce faster. After the influence is exerted, the *influencee*'s post-influence transaction cost is obtained as:

$$T^Y_{TOTAL} = W_p^Y * T_P^{Y(after)} + W_t^Y * T_T^{Y(after)} + W_c^Y * T_C^{Y(after)} + W_e^Y * T_E^{Y(after)}$$

By the logic we have already discussed, it is evident that with every time period, as influence is exerted, T^Y_{TOTAL} of the *influencee* witnesses a negative change. Once T^Y_{TOTAL} < [threshold T^H], the *influencee* "crosses over" to become an influencer him/herself. Gradually, the number of *influencers* rises in the population.

III. AGENT BASED MODELING AND SIMULATION

Agent-based modeling and simulation (ABMS) is a new approach to modeling systems comprised of interacting autonomous agents [22]. Economics is experiencing a paradigm shift in response to agent-based modeling. The field of Agent-based Computational Economics (ACE) has grown around the application of ABMS to economic systems (Tesfatsion, 2005). Some of the classical assumptions of microeconomic theory (e.g all economic agents are rational, agents are homogeneous with identical characteristics and rules of behavior, etc.) are relaxed in ABMS applications to economic systems. Behavioral economics is a relatively new field that incorporates experimental findings on psychology and cognitive aspects of agent decision making to determine people's actual economic and decision making behavior. Thus, agent-modeling is a promising basis for modeling social life as interactions among adaptive agents who influence one another in response to the influences they receive [22].

A. The Simulation Framework

Using agent-based models, we create a virtual population of interacting consumers (network of agents) to study the rate of adoption of on-line shopping by consumers. This virtual consumer population is represented as a network G = (N,L) where N is a finite set of nodes and L is a finite set of bidirectional links. We define ***friends*** of node n as $N_n \in N$, where N_n is the set of nodes ***directly connected*** to n. At any point of time, any node $n_k \in N_n$ can be connected to node n with a link $L_k \in L$.

Each node n is associated with a variable transaction cost T^n_{TOTAL} that indicates its perception of transaction cost towards on-line shopping. When $T^n_{TOTAL} < T^H$ (where T^H is the threshold transaction cost), the consumer will decide to purchase on-line.

Initially, there is a set of nodes $N_I \in N$ with $T^n_{TOTAL} < T^H$ (where $n \in N_I$). These are the Early Adopters of on-line shopping and, in our model, they are the *influencers*. During the course of interaction, they reduce the transaction cost of *influencees*, as described in section II.*C*. As a consequence, an *influencee* becomes an influencer eventually. Progressively, the number of the *influencers* rises in the population. The agent based simulation model that we develop to demonstrate the gradual changes in perceived transaction cost of an individual eventually leads to a global lowering of transaction cost as a result of the influence exerted.

B. The Simulation Set up

The proposed scheme is evaluated on a simulated social network environment under a variety of conditions to estimate the rate of adoption (of on-line shopping) against time. This has been studied using two parameters: Rate of transformation of *influencees* into influencers and rate of change of the average transaction cost of the system.

We present simulations for networks with 10000 artificial consumers (the agents). Each consumer has an average number of friends F which is a variable simulation parameter. Also, we vary the number of *Early Adopters* who will act as *influencers* in the system. The adoption process is initiated when an *influencer agent* interacts with its friends in the network. This process of interaction will influence an *influencee agent* (provided the *influencee agent* is a friend of the *influencer*) to reduce its total transaction cost in favor of on-line shopping, as depicted in section II.*C*. The results are shown below.

These results are, of course, indicative and not validated by empirical studies. To demonstrate the usability of the model, we have generated T_P, T_T, T_C and T_E values randomly. The weights assigned to each agent are also generated randomly. For influencers, the random values are chosen in such a fashion that T_{TOTAL} is less than the threshold T^H.

It is to be noted that this is a model building exercise. However, once equipped with suitable data, we can supply each of these values individually. By examining the parameters and altering them, we can obtain different trends to illustrate how fast influence takes over, how trends vary with country/ town/ population, etc.

C. The Results and Discussions

The graphs obtained from the model use the following parameters:

- No of consumers : 10000
- Average number of friends N_n per consumer in given social network: (i) 10 (ii) 50 (iii) 100.
- Number of Early Adopters (i.e. influencers), I, in given social network: (i) 10 (ii) 50 (iii) 100.
- Commodity factor, S : 0.1
- Value of T_P , T_T ,T_C and T_E:
    - For Influencers: Random value between 1 to 10
    - For Influencees: Random value between 11 to 50
- Value of W_p, W_t, W_c and W_e :
    - Random Value between 0 and 1 such that $W_p + W_t + W_c + W_e = 1$.
- Average Transaction Cost = For all the consumers (from 1 to 10000), $\sum T_{TOTAL} / 10000$
- Transaction Cost Threshold, $T^H = 10.0$

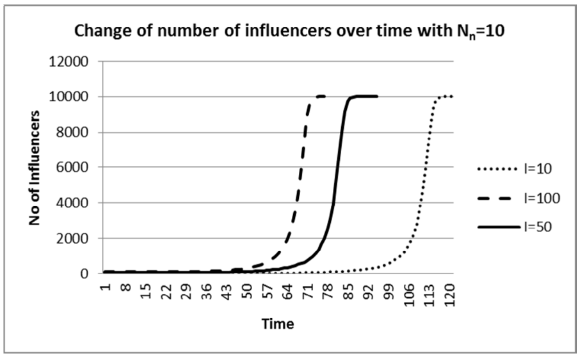

Figure 1. Adoption Process with varying number of Initial Influencers

Figure 1 shows the growth in number of influencers against time under three situations, where initial number of influencers I = 10, 50 and 100 respectively. Average number of friends N_n per consumer is fixed at 10. Once the adoption process crosses a certain threshold, the rate of adoption depends only on number of friends, as evident from the identical growth-rate of the graph after the threshold point. However, the threshold point at the time-scale depends on number of early adopters.

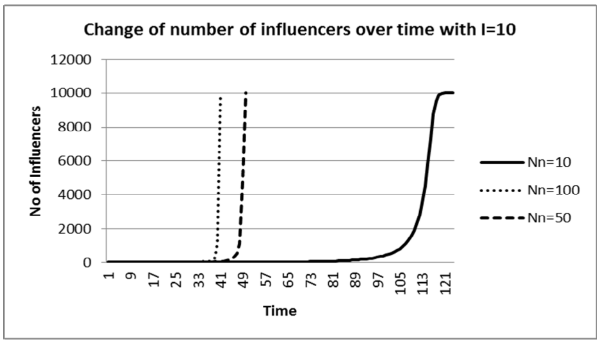

Figure 2. Adoption Process with varying number of friends per consumer

Figure 2 shows the growth in number of influencers against time under three situations, where average number of friends per consumer, N_n = 10, 50 and 100 respectively. As indicated in figure 2, the growth-rate becomes sharper with increase in number of friends. Moreover, the starting point of the adoption process is also dependent on N_n, since a larger number of friends increases the probability of much faster adoption.

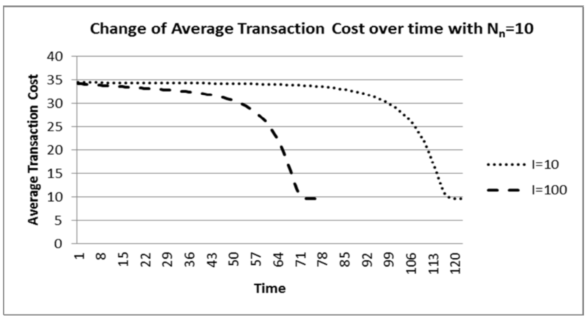

Figure 3. Decrease in Average Transaction Cost with varying number of Initial Influencers

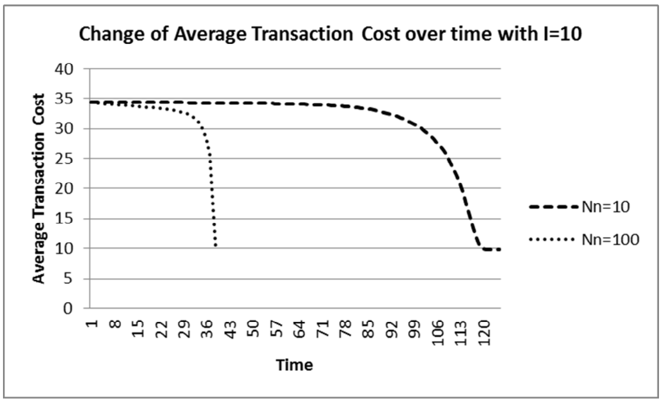

Figure 4. Decrease in Average Transaction Cost with varying number of friends per consumer

Figure 3 and 4 depict the adoption process by showing decrease in the average transaction cost with time. The adoption process is complete, when average transaction cost goes below threshold T^H (=10.0). The nature of the graphs are identical to those in figure 1 and 2.

VII CONCLUSION

In this study, we have demonstrated how social networks accelerate online shopping adoption by constantly altering the transaction costs individuals associate with it. The transition between the "early adopters" (of online shopping) and the "early majority" is covered in a considerably shorter period of time than it would have been in the absence of the social networking effect.

As far as branded and non-perishable items (i.e those items that do not strictly require quality assurance guarantees), electronic goods, or even travel agencies are concerned, online stores offer the obvious advantages of lower prices, hassle-free and quick shopping, and an overall experience of fast and effective transactions that traditional markets fail to deliver in several cases. Thus, an increased number of consumers are opting out of traditional shopping methods. They are guided further by their social network connections, as shown. Brick-and-mortar firms that deal in the aforementioned goods thus need to establish a strong online presence if they are to salvage their existence. Only then can they survive the paradigm shift we have exemplified here.

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