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從模組化偏好到科技創新: 代理人基建模方法
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從模組化偏好到科技創新：代理人基建模方法

From Modular Preference to Technology Innovation:

An Agent-based Modeling Approach

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Abstract

本研究提出代理人基創新模型的研究基礎, 包括偏好模組化的證據與結構。基於本研究, 我們以模組化結構爲前提, 提出一個良好定義的消費者偏好。此偏好可以展現成階層式結構。另一方面, 透過經濟行爲實驗幫助我們說明模組化偏好假設的合理性。

在本研究的第二個主要的部分, 我們建構一個商品市場經濟, 裡頭有一群異質階層模組結構偏好的消費者。存在一個寡占市場結構, 廠商透過尋找消費者心目中的最佳商品設計或生活品質型態以求生存。使用人工智慧經濟學研究中心所開發的模擬軟體, 我們利用遺傳規劃來模擬經濟, 在此架構下, 說明研發與定價策略的角色。

Keywords: 代理人基模型, 模組化偏好, 經濟實驗, 創新

研究目的及文獻探討

Lichtenstein and Slovic (2006) 採納 John Payne 教授的建議, 將決策問題分爲三個層次, 第一, 爲面對完全陌生的環境; 第二, 爲不同屬性之間與我們即有的偏好產生衝突或抵換 (tradeoffs) 的關係; 最後爲將正向與負向觀感明確量化的困難。因此, 除了第一種情形完全只能用猜的之外, 面對第二或第三種情境時, 我們也經常無法明確做出選擇。此時我們內在傾向是否會影響我們判斷的方向。例如: Daniel Ellsberg 教授提出的模糊的厭惡 (aversion to ambiguity), 在面對不確定及沒有額外資訊的情況下, 可預測大部分的人有一個潛在的判斷方向, 這個觀察歸納出人們對即使在不確定之下, 仍然會偏好已知機率的選項, 而對於連機率都不確定的模糊選項顯得趨避。

本研究針對不完全熟悉的情境, 亦即上述第二及第三的層次。這類的決策, 諸如: 選擇新商品、新的工作、遷徙到新環境等不常發生的經驗。通常沒有前例可循的情況下, 人們臨時找到的一些建構偏好的線索成爲影響最後決策的關鍵。無論臨時建構的偏好是否有效, 它的形成仍然可能受到人們過去的經驗及記憶所影響 (Bettman, Luce and Payne, 1998)。因爲這些經驗讓我們知道什麼線索是值得注意的, 例如: 新商品中有些屬性的使用經驗、工作地點的交通不方便的經驗、生活環境附近的公園經常有人爲的噪音。因此對於新的選擇, 過去熟悉的屬性, 無論好壞可能會被賦予較高的權重 (Hsee, 1993)。所以新工作的找尋, 則會考慮交通的便利性; 而新的居住環境, 可能就不會再對公園抱有太大的幻想。

許多文獻證據顯示經驗間接參與新決策的偏好建構 (Ariely and Norton, 2007)。因此, 本研究假設人們面對不完全熟悉的情境並非隨機決策。這些決策和過去累積的習性有關。所以, 我們嘗試以不同的商品屬性誘導消費者偏好並調查商品偏好與人格特性的關係來證明。針對個體差異的部分, 假設個人對商品偏好異質, 根據受試者的選擇行爲, 調查偏好和人格的關聯。同時, 對於人們共同的偏好, 我們假設受試者皆偏好貨幣。基本上, 過去的消費者研究, 僅讓受試者主觀衡量的商品偏好, 研究者並無法再得到受試者的實際選擇行爲, 爲了克服受試者可能言行不一致的問題, 在動機上, 我們提供有效的貨幣誘因來增加實驗的可信度。參加實驗的受試者最後都有機會得到總價值新台幣10,000元的成功升級的商品以及現金。所以, 研究中, 受試者的偏好在共同的貨幣動機驅使下, 也得到共同的比較基礎。希望揭露偏好結構和人格的具體關連。

本研究的限制爲新商品使用的階段, 新的經驗可能會繼續重塑受試者的偏好。因此, 當再面對相同情境時, 可能會做出不同的選擇。這可能會產生言行不一致的問題。然而, 許多因素構成這項研究的限制, 因爲若欲考慮多階段的測試, 需要實現每

位受試者該項新商品, 所耗費的成本恐怕太高。另外,Ariely and Norton (2007) 說明人類決策的行爲並不單純。行爲不僅受到已形成的偏好影響, 也同時受到各種環境因子、過去記憶甚至行爲本身所影響。如果 Ariely and Norton 的假說成立, 外在干擾因素讓我們不易直接觀察眞實的偏好, 因此, 跨期研究的可行性困難度是相當高的。

本報告結構包括, 我們所採用的研究方法, 實驗設計及步驟, 實驗結果及發現還有結論。第二部分代理人基建模的部分請請出席國際會議發表之報告。

研究方法

傳統的經濟分析必須假定消費者偏好已經定義, 再針對各項限制, 求解最適組合(bundle)。換言之, 知道了消費者的動機及其他條件, 就掌握其選擇行爲。因此, 消費者的偏好結構顯得十分重要。掌握關鍵的偏好結構才能正確地解釋消費者的行爲。然而, 若消費者自己連自己的偏好都無法自我描述, 我們如何分析消費者的選擇行爲。這個問題困擾行銷人員很長一段時間, 直到1970年代, 終於有方法可以來瞭解消費者究竟想要什麼。此方法稱爲聯合分析, 乃對特定商品的屬性 (attribute) 及各屬性水準 (level), 以不同組合的方式呈現給消費者做選擇, 再以統計方法推論其偏好結構。文獻上使用的工具爲分解 (decompositional) 模式之聯合分析 (CA, conjoint analysis)。除了分解模式之外, 還包括了組合 (compositional) 模式及混合模式 (hybrid model), 如, 自顯性偏好 (self-explicated) 方法、混合模式聯合分析以及調適性聯合分析 (ACA, adaptive conjoint analysis) 等。

聯合分析發展源自 1964 年數學心理學家 Luce 與統計學家 Tukey 發展出來的聯合衡量 (conjoint measurement)(Luce and Tukey, 1964)。1970年代初由 Green and Rao 引進行銷領域, 聯合分析已經受到學術界和業界相當的重視, 成爲衡量消費者對產品及勞務偏好的方法 (Green and Rao, 1971; Johnson, 1974; Srinivasan and Schocker 1973)。根據 Green and Srinivasan (1978) 爲基礎, 許多和聯合分析相關方法的發展 (Wittink and Cattin, 1989; Carroll and Green,1995, Green and Kreiger, 1991; Mahajan, Green, and Goldberg,1982)。估計1980年初, 每年大約新增 400 個商業應用。其中消費性產品占了將近六成 (Green and Srinivasan,1990)。歸納其應用包括新產品或概念評量、定位、競爭分析、訂價以及市場區隔等爲主。程序的採用以個人訪問資料蒐集爲主流, 透過電腦互動方法來蒐集。使用整體輪廓 (full-profile) 法, 蒐集受試者的評分 (rating scales) 或排序 (rank orders) 資料, 再以最小平方法估計成分效用値 (Green and Srinivasan, 1978)。

隨著商品的複雜化, 屬性和水準的增加使聯合分析的估計愈來愈受到挑戰 (Bradlow, 2005)。自顯性方法、混合聯合分析以及適應性聯合分析陸續發展爲互補的方法 (Green, 1984)。混合聯合分析, 先利用受試者的自顯性偏好值, 將受試者分群, 以降低屬性過多的問題。然而, 產生的估計只能受限於根據自顯性偏好分群後的群體偏好, 無法針對個別消費者偏好的估計。最直接的方法還是組合模式 (compositional model) 的自顯性偏好法 (Huber, 1987), 直接讓受試者分別主觀評量各種屬性、水準以及各屬性的權重, 然後加以組合得到整體的偏好。

然而, 各方法都各自有優缺點, 自顯性方法的潛在問題是當屬性之間存在交互作用, 我們很難要求受試者在假設其他屬性及水準不變之下來做評量。同時, 這裡也可能會出現聯合評量 (joint evaluation) 和分別評量 (separate evaluation) 所可能帶來的偏好逆轉 (preference reversals) (Hsee et al., 1999)。Sattler and Hensel-Borner (2000) 也指出自顯性偏好的限制。第一, 和現實情況的落差, 不同屬性水準可能在整體帶來的效益是同一部分, 在分別看待時將有重複計算的疑慮, 因此, 難以測出成分值之間的非線性關係 (Green and Srinivasan, 1990)。第二, 受試者對於不同水準之間的差異並不敏感 (Von Nitzsch and Weber, 1993) 且容易受到社會一般認爲的方向影響 (Green and Srinivasan, 1990)。第三, 受試者在評分時缺乏動機, 因此, 也較無法直接反應眞實的偏好 (Ding, 2007; Ding, Grewal, and Liechty, 2005)。因此, Park et al. (2008) 提出了升級法來誘導複雜商品的偏好。

實驗設計及步驟

本研究測量淡江大學的大學部以上同學做爲受試者, 其中女生41人, 男生59人, 針對消費性電子產品的偏好結構來做研究。實驗分成兩部分進行資料收集, 人格測驗以及經濟行爲實驗。

賴氏人格測驗

賴氏人格測驗爲賴保禎在1986年, 參考 Guilford (1940), Guilford and Martin (1943), Guilford and Zimmerman (1948) 篩選出 13 個量表。在 2003 年修改爲 15 個量表, 除了原先的 G, A, S, T, R, O, Co, Ag, D, C, I, N, L 之外, 再加入 ST 及 AN 兩個人格特質量表。總題數也擴充到150題, 每個量表 10 題。每一個量表代表一項人格特質, 分別如下: 活動性 (G, general activity), 領導性 (A, ascendancy)、社會外向 (S, social extraversion)、思考外向 (T, thinking extraversion)、安逸性 (R, rhathymia)、變異性 (C, cyclic tendency)、自卑感 (I, inferiority feeling)、神經質 (N, nervousness)、緊張性 (ST, strain)、焦慮性 (AN, anxiety)、憂鬱性 (D, depression)、客觀性 (O, objectivity)、合作性 (CO, cooperativeness)、攻擊性 (AG, aggressiveness)、虛僞性 (L, lie)(賴寶禎與賴美玲, 2003)。

賴氏人格測驗的施測時間並無限制, 一般來說大約40分鐘, 加上計分及講解, 總計約80分鐘。施測完畢後, 休息10分鐘, 進行商品偏好誘導實驗。

自顯性偏好、聯合分析及升級實驗

經濟實驗配合貨幣誘因驅使受試者產生內在的成本效益評量機制。我們以電腦測驗的方式, 依序以自顯性偏好法與聯合分析法, 以及商品升級法, 讓受試者先報告主觀的偏好形態, 接著提供明確的動機讓受試者選擇或組合自己喜歡的商品。以下爲實驗的內容簡介。

由表1 可知, 我們的產品各有3個屬性, 每個屬性有4個水準, 以完全因子設計將產生$4 \times 4 \times 4 = 64$個產品組合。由於受測者對如此數量的受測體進行排序仍然過於龐大, 因此先透過 SPSS 的 Orthogonal Design 程序將產品組合減至最少, 最後找出16個組合。採用整體輪廓模式來進行成份效用值的估計。最後再提供升級的情境讓受試者自主選擇及組合。

升級法步驟:

- 給予受試者初始的商品屬性及水準。
- 受試者被提示所有可以升級的屬性及水準, 每一種屬性僅能升級一次。
- 受試者決定要升級的屬性並且決定欲升級的水準之出價 (WTP)。
- 電腦隨機產生一亂數值 (cutoff), 依據 BDM 方法, 若 WTP $\geq$ cutoff 則可順利升級 (Becker, DeGroot, and Marschak, 1964)。
- 若該屬性沒有升級, 產品的屬性水準將維持不變; 反之, 則會升級到指定的水準。
- 直到所有屬性都升級爲止, 或受試者停止升級活動。

表 1: 產品屬性表

	個人數位助理(PDA)		數位相機 (DC)		多媒體播放器 (MP)	
屬性1	提供的上網型態種類	3G (WCDMA)	畫素	200 萬畫素	支援的影音格式種類	音樂
		3.5G (HSDPA)		300 萬畫素		音樂+照片
		3.5G、WiFi		500 萬畫素		音樂+影片
		3.5G 、 WiFi 及 WiMax		800 萬畫素		支援 rm 影音格式 (即 MP5)
屬性2	GPS 顯示畫面	2D 畫面	螢幕尺吋	2 吋以下	支援的影片畫質	無
		3D 畫面		2.1~2.9 吋		320x240 (近 VCD)
		3D 擬真畫面		3.0~3.4 吋		640x480 (近 DVD)
		2D、3D 分割畫面		3.5 吋以上		1280x720 (HD)
屬性3	記憶體容量	1G	記憶體容量	1G	記憶體容量	1G
		2G		2G		2G
		4G		4G		4G
		8G		8G		8G

實驗結果及發現

自顯性偏好與升級

根據自顯性偏好以及兩階段升級的結果, 我們將100位受試者所選擇的商品分類。分成純產品、純產品記憶體升級、跨產品升級。經過分類, 落在這幾個分類的人數非常分散。表2依照升級的商品分類, 純產品包括 PDA, DC, MP, 以及各自商品單純升級記憶體 (M), 剩下的爲三種商品的各種交集。表2呈現自顯性偏好下的效用值之平均。兩階段升級皆標準化在0到10之間。我們發現除了純產品與數位相機加多媒體播放器之外, 標準化的效用值皆有提升。WTP爲在第二階段升級, 受試者爲了取得另一商品屬性所願付最高價格的平均。在此因爲樣本數的關係, 我們並沒有對新取得的屬性的屬性水準再分類, 所以平均值可能會因爲有些屬性降級而下降。

如果把各屬性及屬性水準分成第一階段升級的 WTP 與第二階段升級的 WTP, 再加以比較。若第二階段升級的 WTP 顯著高於第一階段升級的 WTP, 則表示綜效存在的證據。然而, 因爲樣本數不足的關係, 我們只觀察到 DC 屬性2水準4(3.5吋以上的螢幕), 有顯著性的結果。第一階段升級之樣本數有12, 平均 WTP 爲1633, 第二階段升級之樣本數有10, 平均 WTP 爲2300。使用 T 檢定, 兩者達到p-value $= 0.03$的顯著差異。其餘的屬性及屬性水準雖然兩階段各有消長, 但均不顯著, 除了 MP 的屬性第二階段 WTP 平均值較低之外, PDA及 DC 的屬性在第二階段的平均 WTP 皆較高。顯示若有綜效, 來源較有可能是大螢幕、高畫素、上網及 GPS 的屬性。不顯著的原因還有受試者一開始就先選擇自己效用最高的商品, 因而後續升級的滿足感反而沒有那麼大。如果我們一開始限制受試者選擇某一樣商品, 再自由升級, 可能會有不一樣的結果。另外, 實驗也調查受試者是否存在主觀的綜效, 來源是以問卷的方式得到, 問題內容如下:

> *在第一階段升級完成時:*
> *在進行第二階段升級前, 請先回答以下問題: 無論你是否升級成功, 如果你的理想商品滿分是100分, 在第一階段升級後的商品, 你覺得它帶給你的滿足程度是多少分呢?*
>
> *在第二階段升級完成時:*
> *請再想像一下, 無論你是否升級成功, 如果第二階段升級後的商品帶給你的滿足程度是100分, 那第一階段的商品的滿足程度會變多少分呢?*

我們必須承認受試者可能無法眞實量化其主觀感覺。例如: 大部分的受試者在100分的評分中, 只能精確到10位數。因此, 如果先不論受試者的狀況, 第二階段升級完成時, 所填入的第一階段商品的分數如果小於第一階段升級完成時的分數, 即表示新商品可能產生綜效。換言之, 新商品的

表 2: 實驗結果

	升級1	升級2	變化率	WTP	人數
MP	6.81	n/a	n/a		10
DC	9.31	n/a	n/a		13
PDA	6.70	n/a	n/a		1
MP+M	7.11	7.56	6.33%	1800	5
DC+M	8.39	8.59	2.38%	1388	9
PDA+M	7.55	8.75	15.89%	1250	2
PDA+MP	8.28	8.51	2.78%	2163	8
PDA+DC	8.71	8.83	1.38%	2220	15
DC+MP	8.56	8.56	0.00%	2065	13
PDA+DC+MP	8.15	8.59	5.40%	1909	24

效用超過受試者原先期望理想商品的效用。參與第二階段升級的受試者共有76人, 有綜效者有29人, 約佔參與第二階段升級受試者的38%。

人格與商品選擇

根據受試者主觀所陳述的自顯性偏好, 我們統計受試者升級後的商品接近最適商品的程度。一般來說, 除非受試者有理想的偏好, 否則屬性水準值愈高應該偏好愈高, 同時也應付出愈高的成本。因此, 我們假設最適屬性水準與選擇的屬性水準之間的距離爲受試者希望多保留貨幣的程度。亦即對貨幣的偏好程度。男生在C,I,N,ST,AN,D 等六項人格特徵與貨幣偏好程度存在顯著的負相關。其中 C,I,N 詮釋爲情緒穩定程度, 值愈高代表情緒愈不穩定; ST,AN,D 爲心理健康程度, 愈高代表心理健康不好。所以這次男生的受試者共有59人, 顯示出當情緒愈穩定及心理健康佳的人, 對於貨幣的偏好愈強。這項結果表示男生對於我們提供的3C 商品偏好並沒有十分強, 很有可能大部分的受試者都已經擁有相關的商品。至於情緒較不穩定及心理健康較不好的受試者反而容易受到升級活動的誘導, 不自覺得選了讓自己效用較高的商品。這部分我們還需要比對受試者的問卷資料來確認。

結論

從這些初步的資料, 我們可以約略看出消費者的搜尋能力不僅在於商品本身, 只要我們賦予消費者足夠的彈性, 消費者會根據自身利益及預算找出滿足程度最高的商品。傳統的偏好分析, 在我們的研究可以用商品的其中一項屬性來表現。換言之, 某一商品的偏好, 即對該商品其他屬性不變下, 該消費者對數量屬性的偏好。如今我們假設消費者對某一特定商品的偏好爲多重屬性及不同屬性水準所構成。而且, 更進一步屬性的範圍會隨著消費者的搜尋而擴大, 計算效用的規模也應隨之而放大。這也是目前組合模式和分解模式分析無法解釋及比較超過原定屬性範圍的商品。透過商品升級的誘導, 受試者被告知他們的虛擬貨幣預算有限, 所以他們必須在此有限的預算條件下, 搜尋到最符合自己偏好的商品。同時, 該商品的實際價格隱含在受試者實際獲得商品時需要支付成本。因此動機上, 受試者除了盡可能的滿足自己的需要, 同時也要保護自己的貨幣餘額。我們除了得到商品的組合層次, 還得到了對新屬性的願付價格訊息。

感謝

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RDT08

行政院國家科學委員會補助國內專家學者出席國際學術會議報告

年　　月　　日

<table>
<tr><td>報　告　人
姓　　　名</td><td>池秉聰</td><td>服務機關
及　職　稱</td><td>淡江大學產業經濟學系
助理教授</td></tr>
<tr><td>會議　時間
　　　地點</td><td>2009/7/15 ~ 2009/7/17
University of technology, Sydney, Australia</td><td>本會核定
補助文號</td><td></td></tr>
<tr><td>會 議 名 稱</td><td colspan="3">（中文）　第十五屆國際計算經濟及財務會議

（英文）15th International Conference on Computing in Economics and Finance</td></tr>
<tr><td>發表論文題目</td><td colspan="3">（中文）遺傳運作元與市場篩選: 代理人基建模方法

（英文）Genetic Operator and Market Selection: An Agent-Based Modeling Approach</td></tr>
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報告內容應包括下列各項：

一、參加會議經過

本屆計算經濟協會 (Society for Computational Economics, SCE) 在 *Journal of Economic Dynamics and Control, Journal of Applied Econometrics*, CEPREMAP (Centre Pour la Recherche Econmique et ses Applications), 以及 Quantitative Finance Research Center, University of Technology, Sydney 的贊助下，在悉尼的冬季展開。

大會在會前安排了兩場 Pre-conference workshop 分別邀請到 Prof. Michel Juillard 以及 Prof. Shu-Heng Chen 介紹計算總體經濟學以及異質與多重代理人基建模。

二、與會心得

7 月 13 日由來自 Banque de France and CEPREMAP 的 Juillard 教授利用 Dynare 套裝軟體介紹計算總體經濟學。Dynare 是一種公用的動態隨機一般均衡(Dynamic Stochastic General Equilibrium ,DSGE)的摸擬及估計建模工具。同時 Dynare 亦可以計算最適的政策在這類的模型。它也可以配合 Matlab 或 Octave(一種類似 Matlab 的公用矩陣計算平台)來運行。

Juillard 教授深入淺出的介紹了 Dynare 的基本操作、建模語法、估計演算、以(DSGE)及貝氏估計模型。更高階的應用還包涵了最適政策、交易處理。

7 月 14 日由政大經濟系的 Prof. Chen 介紹異質與多重代理人基建模(Heterogeneous and Multi-Agent Modelling)。內容涵蓋經濟學以及計算科學近一世紀來的發展，包括行為經濟學、實驗經濟學、神經經濟學與代理人基計算經濟學。這些學科的發展彼此的對話目標都是想要瞭解人類的行為。企圖從個體的差異與總體行為之間建立一個描述的管道，其和 Juillard 教授的建模剛好形成對照。前者為由下而上的建模而後者正好相反。最後的目標都是一致的想幫助經濟學家解釋經濟現象，進行提供良好的對策。

兩天密集的 Workshop 之後，大會進入 Parallel Sessions 以及 Plenary Lectures。以下就本次與會所觀察到的內容做重點的陳述。由 University of Amsterdam and Tinbergen Institute 的 Paolo Zeppini 所發表的演化產業模型：耗成本的創新者與便宜的模仿者(Evolution of Industrial Heuristics: Costly Innovators versus Cheap Imitators)。利用動態的建模方法並且和實驗經濟學結合來檢視廠商在耗時耗力的研發創新與簡單的模仿在多廠商的異質商品市場互動。要模仿亦是創新乃是基於互動過程中決定，當有愈多創新者在週遭模仿愈有效。有兩股力量在這中間作用，使得產業歷經不同的情境。產業收斂到一個穩定的均衡是有條件的，價格與廠商的專業亦可能會改變。尤其是當需求受到創新的衝擊而改變，原先的凝聚力將會被打破而形成一種混沌的局面。

由政大人工智慧經濟學研究中心與心理系所聯合籌畫的認知心理在代理人基經濟模型(Cognitive Psychology in Agent-Based Economic Models) Session。提出一個全新的建模思維，經由多階段的受試者資料配合基本的假設以及代理人基建模形成一個多重面向的觀察。從心理學家的工作記憶測驗(working memory test)衡量受試者的工作記憶大小，再經由第二階段受試者的經濟實驗。企圖從人類先天認知的容量來解釋經濟行為。並且再透過代理人基的參數控制模擬出不同的工作記憶代理人。經由兩者的比對獲得了一些支持，雖然還十分粗糙，但就拉近心理學和經濟學之間的對話有相當顯著的貢獻。

大會的 Plenary Lecture 值得注意的是 Cars Hommes 的 The Heterogeneous Expectations Hypothesis: Some Evidence from the Lab 利用不完全競爭市場的架構，同時為了讓受試者(同學)在減低不同的策略運用的複雜情形，讓受試者改以訂價作為策略，中間我們觀察到和以往不同的經濟行為。證明制度的改變可能完全改變經濟的均衡行為。在課程的設計上，也可以輔以經濟實驗加強同學對理論的認識與其侷限。

此次個人在會中發表的 Genetic Operators and Market Selection: An Agent-based Modeling Approach 企圖揭露廠商的創新行為內部的構造，使用的方法是 Genetic Programming, GP。因此，有些技術性的概念透過圖型及表格的呈現成功將本研究的理念介紹給與會的學者。對於我們的模型由於設計的複雜度相當高，許多學者對於模型中的代理人間的互動過程十分感興趣。Prof. Deisseneberg 對於消費者與生產者的議價過程十分感興趣，但是目前本研究仍是較為簡化的設計，也許將來可以再這個地方再多些討論。對於廠商行為的描述，特別是創新行為本研究應該是掌握了相當程度的廠商行為意涵。然而對於 Paolo Zeppini 的模仿行為並沒有辦法描述。克服的方法，需要加入廠商之間的社會學習。同樣的，消費者除了受到創新商品的吸引之外他們之間也沒有互動，這些都是本研究所獲得的建議，成為將來可以參考的重要方向。

最後一天的會議，值得介紹的是來自 National University of Ireland 的 Daniel Paraschiv 所發表的 Algorithmic Trading with Human Agents and Computer Agents in an Artificial Stock Market。他的研究打破過去人工股票市場僅僅侷限於電腦模擬或真人交易，和 U-Mart 類似，他的平台可以讓軟體代理人和真人一起交易。另外特別值得注意的是他使用了多風險性資產的架構，有別於過去傳統模型只有一種風險性資產，在他的模型中可以包括十種風險性資產，受試者可以自行決定投資組合。除了股利是隨機過程所決定，股價均是由軟體代理人和受試者共同決定。可以說是非常接近真實的情境。對於將來本人要進入代理人基財務模型是一個非常重要的典範。

三、建議
無

四、攜回資料名稱及內容
大會議程及摘要一本

五、其他
無

Genetic Operators and Market Selection: An Agent-Based Modeling Approach ⋆

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Abstract

In this study, the simple genetic programming has been modified by the automatically defined terminals. An agent-based two-firm competition market is build to test firms' survivabilities. Through the simulation, we discover the significance of genetic operator rates in product designs by observing its impact on consumer satisfaction and firms' competitiveness.

JEL classification: D20; D43; D83

Key words: Innovation; Agent-based modeling; Automatically defined terminals; Genetic operator

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1 Motivation and Introduction

Extended from our previous studies Chen and Chie (2004, 2006, 2007), which have emphasized *modularity*, we replicate an environment to simulate the evolutionary and innovation process of commodities with *genetic programming* (GP). Meanwhile, the role of *genetic operators* (e.g., recombination and mutation) shall not be overlooked under the GP application. This can be evidenced

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from two extreme examples. One is that the market selects commodities without recombination and mutation; therefore, little improvement can be made. Another is when recombination and mutation occur too often in production so that consumers face different commodities each time choice being made. Commodities with positive elements are replaced with completely new creation. In the latter, knowledge of invention is hard to accumulate and preserve. To remedy this failure, a model with more subtlety is established to simulate the market competition in a two-firm environment. Through large scale simulation, the role of genetic operator in production competencies will also be exploited.

In Chen and Chie (2007), simple GP is modified with modularity approach, which is automatically defined terminals (ADTs). Borrowing the idea of Koza Koza (1994), ADTs have been found to have an affinity for knowledge accumulation. The characteristics of primitive and advanced commodity designs can be captured by ADTs. For instance, it is possible to depict the processing of wheat to flour, and from flour to dough by introducing ADTs. The model also shared the some similarities with Koza's automatically defined functions (ADFs), including hierarchical mechanism, simplicity, and encapsulation.

According to Goldberg (2002), if we combine crossover and selection, continuous innovation will result. In like manner, the combination of mutation and selection is the essence of improvement. However, little discussion has been focused on the impacts brought by different crossover and mutation rates, especially in the area of agent-based economics modeling of innovation. This paper will try to discuss these two genetic operators based on simulation results. Two observations of economic experiments have been carried out. The first one is the contribution of two competitive firms to consumer satisfaction under two different selection pressures. The selection pressure stems from consumer's search intensity, for instance, in a two-firm competition market, consumer should visit both of the firms under high search ability and only visit one of the two firms under low search ability; The second one is the importance of genetic operators in competition among firms. We follow the agent-based model of Chen and Chie (2007) to allow a firm who designs new products with higher crossover rate or mutation rate to compete with the other firm who has lower crossover rate or mutation rate. In a sense, this is equivalent to replicating two different organizational cultures regarding the competition between open-minded and prudent culture.

The rest of the paper is structured as follows. The agent-based model is introduced in Section 2. Section 3 and Section 4 present two experiments with findings, followed by the concluding remarks made in Section 5.

2 The Model

The model is calibrated under a modular economy. In Chen and Chie (2004), we considered an economy of profit-maximizing firms (producers) and surplus-maximizing consumers. Fig. 1 demonstrates the interaction between these two sorts of agents. Producers supply commodities to the market and earn profit/incur loss as a result. Intuitively, each producer is motivated to engage in product innovation and dominate the market through winning more customer satisfaction. This is defined as the “innovation” process, as shown in the green box. Consumers, on the other side, allocate budget in a way to maximize their respective level of satisfaction. *Consumer Surplus* is measured by the difference of maximum willingness-to-pay and the actual price paid for a product. The maximum willingness-to-pay is assessed by given preference, which will be detailed later.

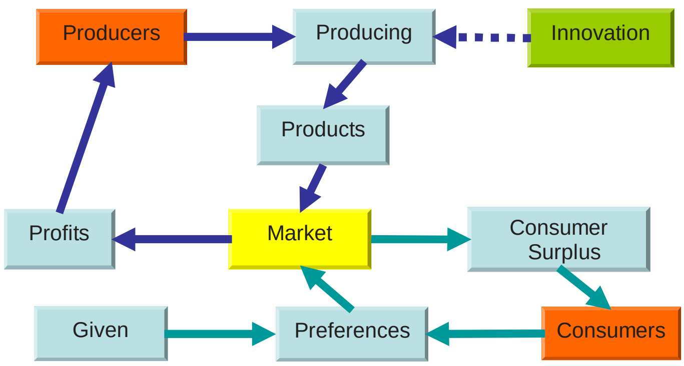

Fig. 1. The agent-based modular economy.

In the following, we will introduce the parameters of *agent engineering* and *environment design*. We first observe the attributes and behaviors of producers and consumers. For example, producers have the capability of *production*, *innovation*, *marketing* and *resource allocation*, which are altogether subject to individual attributes such as *capital limits*, *knowledge*, and *cultural factors*. With a closer investigation, we find that genetic operators play an important role in innovation behavior. Unlike static behavior (e.g., adaptive inventory adjustment), a producer not only perceives market demand through maintaining a variety of product lines, but also evolve and improve the commodities as time goes by. The evolving behaviors are captured by *genetic parameters*. In the meantime, consumers' budget, preference, utility function, and willing-to-pay determine the market demand. The next subsection will discuss the details of parameters.

Producer Parameters

(1) **Working Capital** (k) is a firm's endowment used for production.
(2) **Inventory Adjustment Rate** (λ) adjusts inventory by excess demand (ED) or excess supply of a specific product. The adjustment process can be defined by $q^m_{t+1} = \lambda ED + q^m_t$, where $\lambda \in [0,1]$ and q^m represents quantity of product m.
(3) **Mark-up Rate** (η) is a component of producer's asking price (ask_m), which is calculated as $ask_m = (1+\eta)\bar{C}_m$, where $\bar{C}_m$ is the average production cost of product m.
(4) **R&D Rate** ($\gamma_{R\&D}$) is the proportion of working capital spent on R&D. The R&D working capital ($k_{R\&D}$) is determined by the following formula: $k_{R\&D} = \gamma_{R\&D} \times (k - k_{\text{inv}})$, where k_{inv} is the capital invested in inventory adjustment.
(5) **R&D Ceiling** ($\overline{R\&D}$) defines the maximum usage of R&D resource. Due to the limited market size, R&D expenditure should not increase without boundary.
(6) **Cost per Node** (c) is the unit production cost of using a terminal or function node. It is assumed that the costs of terminal and function nodes are the same.

Consumer Parameters

(1) **Consumer Income** (I) is a consumer's endowment exogenously given at the beginning of each period, which usually has a crucial impact on market demand.
(2) **Depth of Preference** (d_p) defines the total tree depth of a consumer's preference. The deeper the preference, the more sophisticated a consumer may be.
(3) **Depth of Common Preference** (d_c) is the depth of identical preference tree structure shared among all consumers.
(4) **Base of Preference to Utility** (z) is a component of the utility function. It is normally greater than 2 to ensure the *synergy effect.* [1]
(5) **Price to Utility Ratio** (v) determines a consumer's subjective valuation of a particular product, which is also known as the *willingness-to-pay* (i.e. bid). It is calculated as $bid = v \times U_m$, where U_m is the consumer's utility level for product m.
(6) **Search Intensity** (r_s) is the percentage of total producers that will be selected. In other words, the selection intensity determines how many producers will be visited by a consumer, which is calculated as $r_s \times n_p$.

[1] The synergy effect of the consumer preference is defined in Section 2.3.

Genetic Parameters

(1) **Initialization of Tree**. According Koza (1992), there are three methods to initialize a tree population. They are *growth method*, *full method*, and *ramped half-and-half method* (a mixed of the growth and full method). In this paper, we use full method to set consumer common preference, and the ramped half-and-half for heterogeneous preference and commodity.
(2) **Number of Primitives** (ρ) is the size of terminal set and function set.
(3) **Initial Tree Depth** (d_{ini}) restricts the depth of the first generation commodity tree. [2]
(4) **Maximum Tree Depth** (d_{max}) describes the maximum commodity tree depth allowed in this simulation. In order to satisfy consumer preference, it is normally higher than d_p and is limited to computer capacity (e.g., memory size).
(5) **Tournament Size Ratio** (r_{ts}) determines the tournament population (POP^j_{ts}) size used to run genetic operators. It is defined as $POP^j_{\text{ts}} = r_{\text{ts}} \times POP^j$, where POP^j represents the whole commodity population of producer j.
(6) **Crossover Rate** (p_c) is the probability of recombining the most two profitable commodity trees in the tournament population.
(7) **Mutation Rate** (p_m) is the chance to alter offspring's terminal or function nodes or sub-trees after crossover.
(8) **Automatically Defined Terminal** (ADT) is a prototype which can be used to produce higher level of commodities. [3]

2.2 Environment Design

This subsection introduces the underlying *learning cycle* and *market rules* for firms and consumers. As mentioned earlier, a firm may maximize profit by producing various products, hereby learning consumer preference. As shown in Fig. 2, the GP driven innovation process constitutes a series of new products launched every generation. In this paper, the model runs 5,000 generations, each calibrating with five trading days. After each learning cycle, a firm determines what to produce (including new products developed via product innovation), how many to produce, as well as the price to charge for the next generation. Such decision is based on the feedbacks (e.g. sales and profit statistics) collected from the previous generation.

The trading between buyers (consumers) and sellers (producers) is also regu-

[2] Due to the lack of market (demand) information, this setting captures the initial stage of producers' behavior, which is to produce less complex and more diverse commodities.
[3] See Chen and Chie (2007) for details.

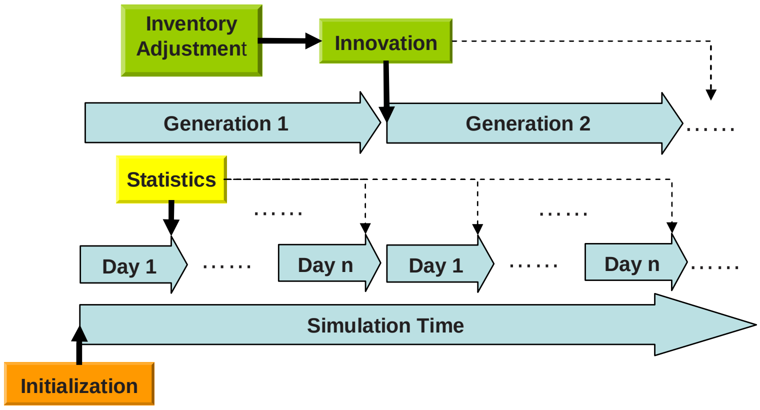

Fig. 2. Market days and learning cycles.

lated by some market rules. First, a buyer will research all available products in the marker before making a purchasing decision. The pricing strategy established by the sellers is a *take-it-or-leave-it* offer based on respective cost and mark-up rate. A buyer's strategy, on the other hand, is to maximize consumer surplus which can be defined as:

$$\max(bid^i_m - ask^j_m),\ \forall j, m \tag{1}$$

and a transaction can be described as

$$buy^{ij}_m = \begin{cases} 1 & \text{if } bid^i_m \geq ask^j_m \text{ and } q^j_m > 0 \\ 0 & \text{otherwise.} \end{cases}$$

where buy^{ij}_m is a binary indicator. When it equals one, a transaction will be carried out, and the price of product m will be $P^j_m = ask^j_m$; otherwise, no transaction will take place. If, however, product m was sold out (i.e., $q^j_m = 0$), the consumer will select the second best choice and the rest may be deduced analogously until $bid^i_m < ask^j_m$. The shortage of product m will then be recorded in the log as *exceed demand* by producer j. In other words, each consumer will at most purchase one product in each trading day. In addition, to avoid negative shopping experience, a consumer's failing to purchase a commodity from a seller today may lower the probability of his or her meeting the same seller tomorrow, which can be described as

$$\text{Prob}_{ijk} = \frac{1 + \sum_{i=1}^{k} buy^{ijk}_m}{k + n_p}. \tag{2}$$

where Prob_{ijk} is the probability that consumer i has met producer j for k times, and n_p is the number of producers. The search intensity (r_s) of a consumer also plays an important role in the trading process. The search space for a consumer is denoted by $\text{round}(r_s \times n_p)$, where round() represents *round-off*

Table 1
Parameter Settings

Parameter	Tyep (Variable)	Range	Default Value
	Producer		
Number of Producers	Integer (n_p)	[1, ∞)	1
Initial Working Capital	Integer (K_0)	[1, ∞)	500
Working Capital per Gen.	Integer (K)	[1, ∞)	500
Inventory Adjustment Rate	Real (λ)	[0, 1]	80%
Mark-up Rate	Real (η)	[0, ∞)	100%
R&D Rate	Real ($\gamma_{\text{R\&D}}$)	[0, 1]	1%
R&D Ceiling	Real ($\overline{\text{R\&D}}$)	[0, ∞)	500
Cost per Node	Real (c)	[0, ∞)	1.0
	Genetic Operator		
Number of Primitives	Integer (ρ)	[1, ∞)	5
Initial Tree Depth	Integer (d_{ini})	[1, ∞]	5
Maximum Tree Depth	Integer ($d_{\max}$)	[1, ∞]	11
Tournament Size Ratio	Real (r_{ts})	[0, 1]	10%
Crossover Rate	Real (p_c)	[0, 1]	90%
Mutation Rate	Real (p_m)	[0, 1]	80%
Automatically Define Function	Boolean (ADT)	T, F	T
	Consumer		
Number of Consumers	Integer (n_c)	[1, ∞)	100
Consumer Income per Gen.	Integer (I)	[1, ∞)	10000
Depth of Consumer Preference	Integer (d_p)	[1, ∞]	6
Depth of Common Preference	Integer (d_c)	[1, d_p]	5
Base of Preference to Utility	Integer (z)	[2, 10]	4
Price to Utility Ratio	Real (ν)	[0, ∞)	5.0
Search Intensity	Real (r_s)	[0, 1]	100%
	Time Schedule		
Trading Days per Gen.	Integer (Day)	[1, ∞)	5
Number of Generations (Gen.)	Integer (Gen)	[1, ∞)	5000

function.[4] When $r_s < 100\%$, only portion of the producers may be included in a buyer's shopping list. For example, if there are two producers and a hundred consumers, and `consumer 1` has completed eight shopping experiences, which are zero bad and five good transactions with `producer 1` and two bad and one good transactions with `producer 2`, the consumer's updated probabilities for the two producers are $[\text{Prob}_{115}, \text{Prob}_{123}] = [0.86, 0.4]$. After re-scale the probability $[\text{Prob}_{115}, \text{Prob}_{123}] = [0.68, 0.32]$, and then when $r_s = 0.5$, the consumer will have more tendency to choose `producer 1` next time. In other words, in the case of $r_s = 100\%$, the value of Prob_{ijk} will not affect the search space of a consumer, because all the producers will be visited by each consumer. Table 1 summarizes the parameters applied in this model.

[4] The function rounds off $r_s \times n_p$ to the nearest integer.

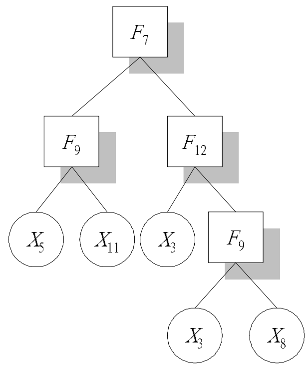

Fig. 3. An illustration of a product.

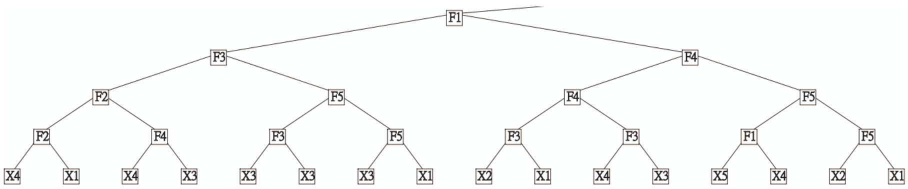

Fig. 4. An illustration of the common preference of a consumer.

2.3 Commodity and Preference

The commodity in the model is represented as a *parse tree* which is shown in Fig. 3. Each parse tree corresponds to a LIST program.[5] The terminal leaves correspond to the raw inputs (materials) $X1$, $X2$, ..., whereas the root and all intermediate nodes represent the processors, $F1$, $F2$, ..., applied to these raw materials in a bottom-up order, as the usual behavior of a LIST program. The whole parse tree can, therefore, be interpreted as a production process associated with the commodity. The unit cost of the commodity is a function of the number of processors and the number of raw inputs, i.e., it is a positive function of the node complexity of the commodity. In a simpler way, we assume that the unit cost is a linear function of the node complexity.[6]

The preference of the consumers is also represented by a GP tree. To make the preference tree well-behaved in economics, three assumptions have been made in Chen and Chie (2004), namely, the *monotone, synergy*, and *consistency condition*. In our simulation, there are 100 consumers in the market. Each consumer has a preference tree with a depth of six. Viewed from the topmost level (the root level), the preference tree is composed of two modules. The one on the left, having a depth of five as shown in the Fig. 4, is identical

[5] In the case of Fig. 3, the product can be represented as a LIST program form, $(F_7(F_9X_5X_{11})(F_{12}X_3(F_9X_3X_8)))$.

[6] The cost function can be defined by $C(N)$, where N is the used number of functional and terminal nodes. The positive function is defined by $\frac{dC}{dN} > 0$, and the linear function is defined by $\frac{dC}{dN} = c$, where c is a constant.

among all consumers, whereas the one on the right, having a depth of five or less, is heterogeneous, and is randomly generated by the ramped half-and-half method, an initialization method frequently used in GP. In this way, consumers' preferences have a common part as well as an idiosyncratic part. The example of an idiosyncratic part is shown in Table 2.

The utility of consuming a commodity is based on measuring the degree of similarity between commodity and preference. Chen and Chie (2006) has developed a module-matching algorithm to perform the task of matching each commodity module (subtree) with each preference module in a descending order relating to the depth of the tree. Under this mechanism, the biggest module will be processed first; if it is successfully matched, the process will stop, otherwise, it will proceed to process the second biggest commodity module until the commodity modules are exhausted. To satisfy the synergy condition and hence the idea of added-value, Chen and Chie (2006) assumes a power utility function for the preference tree as

$$U(S_{d,j}) = \begin{cases} z^{d-1}, & \text{if } j \text{ is matched} \\ 0, & \text{otherwise,} \end{cases} \tag{3}$$

$$U = \sum_j U(S_{d,j}). \tag{4}$$

Each of the modular preference ($S_{d,j}$) is sorted by the depths (d), where j is the index of the subtree. The raw utility $U(.)$ is generated by Equation (3) with base z, where $z \geq 2$. As a result, the utility U is exponentially increasing when higher levels of modular preferences are satisfied. To demonstrate the utility calculation, we use the product in Fig. 3 and the idiosyncratic preference in Table 2 as an example. The first biggest commodity module is the commodity itself, which is $(F_7(F_9X_5X_{11})(F_{12}X_3(F_9X_3X_8)))$. However, it fail to match any one of preference module in Table 2. Then we try the next biggest commodity module, which is $(F_{12}X_3(F_9X_3X_8))$. It still match none of the preference module. The process stops when the next commodity module $(F_9X_3X_8)$ and $(F_9X_5X_{11})$ match with $S_{2,1}$ and $S_{2,2}$ respectively. It should also be noted that there is another commodity element X_3 matches preference at the first level of depth. As a result, as Equation (3) shows, the commodity total gets 5 units of utility from the idiosyncratic preference.

Table 2
An example of idiosyncratic modular preference ($z = 2$)

Depth (d)	Subtrees or terminals	$z^{(d-1)}$
1	X_3, X_5, X_8, X_{11}	1
2	$S_{2,1} = (F_9X_3X_8)$ $S_{2,2} = (F_9X_5X_{11})$	2
3	$S_{3,1} = (F_5X_3(F_9X_5X_{11}))$	4
4	$S_{4,1} = (F_2(F_9X_3X_8)(F_5X_3(F_9X_5X_{11})))$	8
5	$S_5 = (F_6X_3(F_2(F_9X_3X_8)(F_5X_3(F_9X_5X_{11}))))$	16

3 Market Selection and Consumer Satisfaction

Table 3
Parameters of Search Intensity

Parameter	Type (Variable)	Range	Value
	High Search Intensity		
Number of Firms	Integer (n_p)	[1, ∞)	2
Search Intensity	Real (r_s)	[0, 1]	100%
	Low Search Intensity		
Number of Firms	Integer (n_p)	[1, ∞)	2
Search Intensity	Real (r_s)	[0, 1]	50%

Note: The rest of the parameter settings are the same as Table 1.

This section explores the influence of two kinds of consumer search abilities, presented in Table 3. With low selection pressure, each consumer meets only one of the two firms. On the contrary, it is found that high selection pressure may foster the meeting of both firms on every trading day. With limited market demand, the higher the search intensity, the higher the market selection pressure.[7] For purpose of further analysis, statistics about consumer satisfaction in each generation are reported. Consumer satisfaction is normalized by dividing the consumer surplus received from consumption with the maximum potential surplus of the consumer, multiplied by 1000. In other words, the normalized value will lie in [0, 1000]. Averaging the consumer satisfaction over all 100 consumers, we then derive the aggregate consumer satisfaction, which also lies in the same interval. The result is shown in Fig. 5, which is the maximum average value of all the experimental runs. Since the variation of high search intensity case is much larger than the low search intensity one, we collected 100 runs for the former and 50 runs for the latter to achieve statistical validity. As illustrated in Fig. 5, consumer satisfaction rises with his or her own search ability. However, the survivability of these two firms is rather different. Both firms can survive under low selection pressure, but the situation changes dramatically under high selection pressure. Under the severe selection pressure scenario, usually one firm survives. Nonetheless, after examining the all experimental results, the chance of the success in either case do not have significant difference. In the next section, we will further investigate the parameters of genetic operator from a competitive advantage point of view.

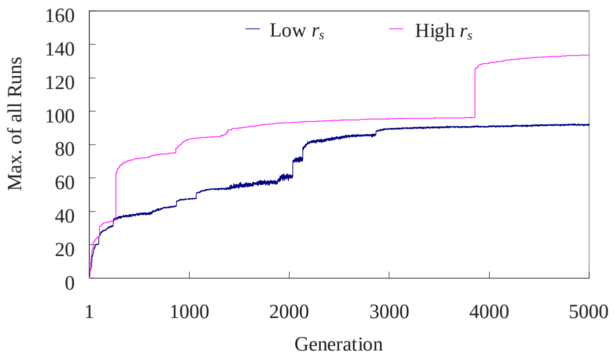

Fig. 5. Time series of consumer search intensity and consumer satisfaction.

Table 4
Parameters of Genetic Operator Rates

Parameter	Type (Variable)	Range	Value
	Crossover Rate Competition		
Number of Firms	Integer (n_p)	$[1, \infty)$	2
Crossover Rate	Real (p_c)	[0, 1]	(1) 45% (2) 90%
	Mutation Rate Competition		
Number or Firms	Integer (n_p)	$[1, \infty)$	2
Mutation Rate	Real (p_m)	[0, 1]	(1) 40% (2) 80%

Note: (1), (2) are the parameters for low-rate firm and high-rate firm respectively.

4 Genetic Operator and Competitiveness

As shown in the previous section, compared to the low selection pressure environment, high selection pressure not only brings more consumer satisfaction but increases the overall market competition as well. To understand how genetic operators may influence a firm's competitiveness and hence the level of market competition, we have further investigated the effects of crossover rates and mutation rates in a high selection pressure setting of two firms. We have considered the following two scenarios:

- Scenario 1: High crossover rate (90%) versus low crossover rate (45%)
- Scenario 2: High mutation rate (80%) versus low mutation rate (40%)

Table 4 has summarized the relevant parameters.[8] With simulation, the survivability (which is positively correlated to competitiveness) of the two firms under different settings can be unveiled through monitoring respective market share at different time horizon. Market share is calculated as the total sales of each firm divided by the total sales of the market.[9]

[7] Note that our consumers are allowed to buy at most one commodity each trading day.
[8] The rest of the parameter settings are the same as Table 1.
[9] As a firm may produce more than one product, its total sales are normally generated from a bundle of products. Similarly, the total sales of market is measured

In this study, we have simulated 100 runs for each scenario. Results of the two scenarios can be found in Fig. 6. Means of the 100 runs are presented on the left, whereas the medians are on the right. The shaded area represents the market share of the low-rate firm as time goes by; the complement is the market share of the high-rate firm. As can be seen, the low-rate firm seldom owns more than half of the market share and hence is dominated in a market of high competition. This coincides with our earlier finding that when the selection pressure is high, usually one of the two firms dominates the market. Despite the rates under investigation, it is also found that the behaviors of the two kinds of time-series are rather different. While the means are relatively smooth below the midline, the medians imply that competition may cause more extremity overtime.

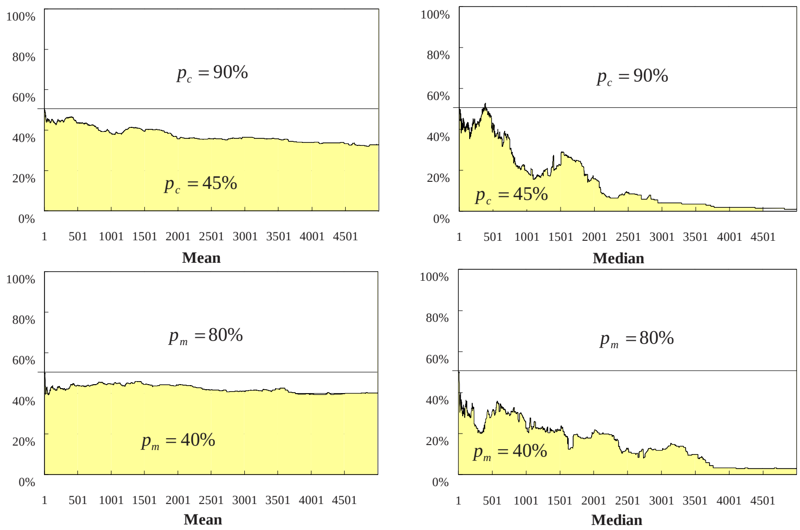

Fig. 6. Genetic operator rates and competitiveness.

In addition to the above findings, we would like to interpret the impacts of genetic operators from an economic point of view. Crossover describes the activity of exchanging information, whereas mutation is the process of deviation from former position. Higher crossover rates raise the probability of information-exchanging and encourage recombining innovative ideas. Although crossover and mutation sometimes may bring destructive results, they have been found useful in discovering and preserving good ideas. This has also been suggested by Goldberg (2002) in his book "The Design of Innovation."

With genetic operators, it is possible to simulate the impacts of various organizational cultures or attitudes. For example, a progressive (e.g. high-rate) firm may supply more innovative commodities to the market and face more uncertainty in selling those products. Meanwhile, a conservative (e.g. low-rate) firm may adhere to former designs, failing to catch up with market trend. As

based on all the available products in the market at a particular point of generation.

a result, it is likely that a low-rate firm would be driven out of market due to loss of consumer satisfaction.

5 Concluding Remarks

Consumers and firms behavior can be studied and the patterns can be extracted. In this paper, we studied the significance of genetic operators in product innovation and market selection. Two observations have been found in this study. First, selection pressure is positively correlated with consumer satisfaction. The more the pressure experienced in a firm's production, the higher the satisfaction level of a consumer can achieve. Selection pressure is defined in terms of the number of choices consumers have. If no choice being granted, products with low quality or little invention may still be selected. However, the more the choices, the better a consumer becomes enhanced of his or her own satisfaction.

In addition, parameters of genetic operator are crucial in determining the competencies of producers. In our agent-based two-firm model, two producers with different crossover and mutation rates compete with each other in innovation. It is found that product innovation takes not only modularity but also proper settings of genetic operator. Various parameters of genetic operator may represent different organizational cultures. This mechanism provides an opportunity to observe the competition between an open-minded culture and a more conservative one.

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A Appendix

Pseudo Code:

```
Initialize Market, Consumers, and Firms
Ask Firms [ Initialize Commodities
           Pricing Commodities
           Waiting for Consumers ]
Do While day mod 5 <> 0 [
Ask Consumers [ Decide Shopping List
               Visit Firms on Shopping List
               Buying Commodities
               Update Experiences of Visited Firms
               day ++ ] ]
Do While generation < 5000
[
  generation ++
  Ask Firms [ Acquire Statistics
             Adjust Inventory
             Innovation
             Pricing Commodities
             Waiting for Consumers ]
  Do While day mod 5 <> 0 [
  Ask Consumers [ Decide Shopping List
                 Visit Firms on Shopping List
                 Buying Commodities
                 Update Experiences of Visited Firms
                 day ++ ] ]
]
```