A Dynamic Adoption Model with Bayesian Learning: Application to the U.S. Soybean Market *

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Abstract

Agricultural technology adoption is often a sequential process. Farmers may adopt a new technology in part of their land first and then adjust in later years based on what they learn from the earlier partial adoption. This paper presents a dynamic adoption model with Bayesian learning, in which forward-looking farmers learn from their own experience and from their neighbors about the new technology. The model is compared to that of a myopic model, in which farmers only maximize their current benefits. We apply the analysis to a sample of U.S. soybean farmers from year 2000 to 2004 to examine their adoption pattern of a newly developed genetically modified (GM) seed technology. We show that the myopic model predicts lower adoption rates in early years than the dynamic model does, implying that myopic farmers underestimate the value of early adoption. My results suggest that farmers in my sample are more likely to be forward-looking decision makers and they tend to rely more on learning from their own experience than learning from their neighbors.

Keywords: technology adoption, Bayesian learning, structural estimation

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1 Introduction

Many researchers model agricultural technology adoption as a binary choice problem: farmers choose to either adopt a new technology or not at all (e.g. Cameron, 1999; Barham et al., 2004; Useche, Barham and Foltz, 2009). This assumption allows researchers to use the Logit or multinomial Logit model to analyze the adoption process. However, in reality farmers may behave in a sequential or "stepwise" fashion. They may choose to apply the new technology on part of their land first, and then adjust their adoption in later years after observing the outcome from the partial adoption, or, if applicable, farmers may adopt selected components of the new technology package first and then adjust later upon learning (Leathers and Smale, 1991). For example, during the "Green Revolution" the new agricultural technologies included new seed varieties, optimal fertilizer usage and other cultivation requirements. "Farmers...experiment with recommendations, often adopting them in stages rather than as a complete package" (Cummings, 1975, p.24). A similar pattern is observed in farmers' adoption path of the newly developed genetically modified (GM) seeds since the mid-1990s. Farmers rarely switch all their land from conventionally bred seeds to GM seeds immediately. Rather, the adoption process follows a gradual transition pattern and farmers end up with full adoption, partial adoption or no adoption after about 15 years since the inception of the new technology. [1]

What factors have driven such an adoption pattern? Indeed, technology adoption is likely a dynamic process, as it involves risk management, learning behavior as well as investment adjustment (Griliches, 1957; Barham et al., 2004). Such a dynamic process essentially implies that farmers are forward-looking, i.e., they take account of the possible future benefits or costs when making current adoption decisions. If the new technology entails uncertainty

[1] Note the difference between sequential adoption and partial adoption in equilibrium. Partial adoption in equilibrium is due to the heterogeneity in farmers' land, such that part of their land may not be suitable for the new technology. Sequential adoption focuses on the process, i.e., why it takes several years to reach the "equilibrium" level of adoption.

and high potential risk in yield or profitability, one possible future benefit of farmers' experimenting with partial adoption today could be their updated knowledge about the new technology through learning. With the potential future benefits in mind, it is possible that farmers adopt a new technology in part of their land even when it appears less profitable than the traditional technology during the initial periods. If farmers are not forward-looking, i.e. being "myopic", then they will only adopt a new technology if it generates greater current benefit than that of the traditional technology. The myopic farmers will then exhibit a lower rate of early adoption compared to the forward-looking farmers because they underestimate the value of early adoption by ignoring the potential future benefits. Or the myopic farmers may over-adopt in the early periods if they ignore the future costs associated with the technology, therefore overestimate the value of early adoption of the new technology. It is possible to observe both types of farmers in the real world. For example, a family farm with a long history may be likely a forward-looking farmer, while a farmer with a short-run land tenure contract may be likely a myopic farmer.

Researchers have worked hard in trying to understand the technology adoption process in agriculture. Following Griliches (1957), early adoption literature on agricultural technology focus on how heterogeneity in farm land and the characteristics of farmers affect adoption decisions. For example, Feder, Just and Zilberman (1985) conduct a survey of the literature on agricultural technology adoption and suggest that farm size, risk and uncertainty, human capital, labor availability and the credit constraint contribute to differences in the adoption process. A recent work by Useche, Barham and Foltz (2009) employs a mixed multinominal Logit model to investigate the effect of heterogeneity in both farmers and the GM corn seeds on farmers' adoption decisions. Their results show that farmers adopt different types of GM seeds according to their preferences on different traits embedded in the seeds.

Recent literature has started to recognize the dynamic nature of the adoption process and to incorporate the learning component into the adoption model (e.g. Besley and Case, 1994; Foster and Rosenzweig, 1995; Baerenklau, 2005). Both Besley and Case (1994) and Foster and Rosenzweig (1995) model the adoption of high-yielding seed varieties (HYVs) with learning in India during the Green Revolution era. Besley and Case (1994) find that the cooperative learning model fits their data the best while the myopic model the worst. Foster and Rosenzweig (1995) explicitly model farmers' learning of the optimal target input and focus on the effect of self-learning versus learning from neighbors. Both papers confirm that imperfect knowledge of the new technology inhibits adoption and farmers' learning can reduce uncertainty significantly. Baerenklau (2005) builds a similar adoption model with a focus on risk preference, learning and peer-group influences. He applies his model to a group of Wisconsin dairy farmers and finds that risk preference and learning are the key factors in driving technology adoption, and that peer-group influence plays a less important role than self learning.

In this paper we construct a continuous choice dynamic model where forward-looking farmers learn the profitability and the risk of a new technology by experimenting on part of their land. Based on their Bayesian beliefs regarding the risk of the new technology, farmers solve a finite period dynamic programming problem to choose the amount of land to allocate to the new technology in each time period. Unlike the previous literature that focus on the learning of the mean profit (e.g. Foster and Rosenzweig, 1995; Besley and Case, 1994), my model focuses on the learning of the variance, or the risk associated with the new technology. Moreover, in my structural model estimation, all the parameters in the dynamic model are recovered by searching within the whole parameter space, which differs from the previous dynamic adoption literature that either rely on reduced form estimation recovering only part of the parameters (e.g., Foster and Rosenzweig, 1995) or conduct the parameter searching within limited parameter space only (e.g. Besley and Case, 1994; Baerenklau, 2005).

My model is applied to a panel of U.S. soybean farmers from year 2000 to 2004. Two types of seed technologies are present in the U.S. soybean seed market: the conventionally bred seeds and the GM herbicide tolerance seeds. For the same sample of farmers, we estimate both a myopic model and a dynamic model and compare results from both models. We find that the myopic model estimation predicts lower adoption rates during early years than the dynamic model estimation, which is consistent with the belief that myopic farmers underestimate the value of early adoption. The predicted adoption pattern from the dynamic model fits the observed adoption path better than that from the myopic model, suggesting that these farmers are more likely to be forward looking. My results also show that for these farmers, self learning affects adoption decisions more than the learning from their neighbors does, which confirms findings regarding the role of social learning in the existing literature (e.g. Besley and Case, 1994; Foster and Rosenzweig, 1995; Baerenklau, 2005).

The rest of the paper is organized as follows. Section 2 presents the model, where we specify the distribution of returns from two technologies: a conventional technology and a new technology, and construct farmers' Bayesian learning process accordingly. We describe the data in Section 3. In Section 4 we explain the estimation strategies for both the myopic model and the dynamic model. Section 5 presents the estimation results and the interpretation. The last section concludes.

2 An Adoption Model with Bayesian Learning

Suppose farmers face with two technologies: an existing conventional technology (old) and a newly developed technology (new). We assume that the profits of both technologies are random, i.e., both technologies are risky assets for farmers. If farmers are myopic, they will choose the adoption rate of each technology only to maximize their current benefits. However, if farmers are forward-looking, they will choose a sequence of adoption rates to maximize their total discounted benefits across time.

2.1 A Mean Variance Framework

Suppose for each farmer the total profit π is normally distributed, then the expected utility $u(\pi)$ can be expressed as a function of the mean and variance of the profit (Huang and Litzenberger, 1988, p.61) , so for farmer i

$$u_i(\pi) = f(E[\pi], \sigma^2(\pi)) \, ,$$

where $E[\pi]$ and $\sigma^2(\pi)$ are the expectation and the variance of total profit respectively. Assume function $f(\cdot)$ to be linear as

$$f(E[\pi], \sigma^2(\pi)) = E[\pi] - \frac{1}{2}\beta_i \, \sigma^2(\pi) \, ,$$

where β_i is a measure of the degree of farmer i's risk aversion and is specified as

$$\beta_i = \beta_0 + \frac{\beta_1}{A_i} \, ,$$

with A_i the farm size of farmer i, and β_0, β_i the corresponding parameters. Then, we can write the expected utility of farmer i as:

$$u_i(\pi) = E[\pi] - \frac{1}{2}\beta_i \, \sigma^2(\pi) = E[\pi] - \frac{1}{2}\left(\beta_0 + \frac{\beta_1}{A_i}\right) \sigma^2(\pi) \, . \tag{1}$$

The distributions of profits from the old and the new technology are specified as follows.

2.1.1 Distribution of Returns

Assume both technologies being seed technology: the old one being the conventional seed and the new one being the GM seed. The profit per unit of land is assumed to be normally distributed. For conventional seed, since it has been planted for many years, we assume the distribution is known to farmers:

$$Conventional \qquad \pi_c \sim N(\mu_c, \sigma_c^2)\,.$$

For GM seed, the profit at time t for farmer i is assumed to be

$$\pi_{igt} = \mu_g + \varepsilon_{igt}\,,$$

where μ_g is the average profit of GM seed, and ε_{igt} is an independently and identically distributed normal random variable with mean zero and variance σ_ε^2. The error term ε_{igt} may include the effect of rain fall, soil conditions, unobserved individual farmer characteristics, etc., on the average GM profit across farmers and time, thus it is known to farmers but unobservable to econometricians. Farmers, however, can only perceive the average profit of GM seed μ_g with uncertainty, and their beliefs follow a normal distribution $\mu_g \sim N(\mu_{igt}, \sigma_{igt}^2)$, which can be updated over time based on their own experience and the information they may obtain from neighbors.

Specifically, the learning process is: at time zero, farmer i receives exogenous information on μ_{ig0}, for which farmer i believes its accuracy can be measured as σ_{ig0}^2; At time 1, if it is profitable, farmer i may experiment with the GM seed on part of his or her land, and then update his or her beliefs on both parameters as μ_{ig1} and σ_{ig1}^2, based on learning from the field experiment. Meanwhile, farmer i observes his or her neighbors' behavior and may also learn from that information to update μ_{ig1} and σ_{ig1}^2. This learning process keeps going until it reaches the steady state.

2.1.2 Update the Variance σ^2_{igt} of the Perceived GM Average Profit μ_g

So for farmer i at time t, the total variance of the profit from planting GM seed is

$$\sigma^2(\pi_{igt}) = \sigma^2(\mu_g) + \sigma^2(\varepsilon_{igt}) = \sigma^2_{igt} + \sigma^2_{\varepsilon}\,. \tag{2}$$

The profit variance induced by the disturbance ε_{igt}, σ^2_{ε}, cannot be reduced by farmers' effort of learning. σ^2_{igt}, however, can be reduced by learning from experiments. The term σ^2_{igt} can be interpreted as farmer i's perceived variance of the GM profit or the uncertainty associated with adopting the GM seed. Since GM is a new technology, the uncertainty is high and farmers may perceive a high variance with its profitability initially. This perceived variance may decrease over time if farmers learn about this new technology by experimenting on part of their lands and/or by communicating with their neighbors. For example, Figure 1 illustrates a possible path of the perceived variance of GM profit over time with a constant belief on the mean: at time 0, farmers' perceived variance of μ_g is high; With experiments over time, farmers become less uncertain about μ_g and the perceived variance σ^2_{igt} become lower as time t increases.

If the learning process of each farmer follows a Bayesian setup, then farmer i updates his or her perceived profit variance of GM seed in the following way [2]

$$\sigma^2_{igt+1} = \frac{1}{\frac{1}{\sigma^2_{igt}} + \frac{G_{it}}{\sigma^2_{\varepsilon}} + \frac{G_{-it}}{\sigma^2_{\varepsilon}+\sigma^2_{\xi}}}, \tag{3}$$

where G_{it} is farmer i's total adopted units of land of the GM seed at time t, G_{-it} is the average adopted total units of land of his or her neighbors, σ^2_{ξ} is the additional variance in farmer i's learning from neighbors. This formula implies that if farmer i does not adopt any GM seed at time t, and does not obtain any information from his or her neighbors, his or her

[2] See Appendix A for details.

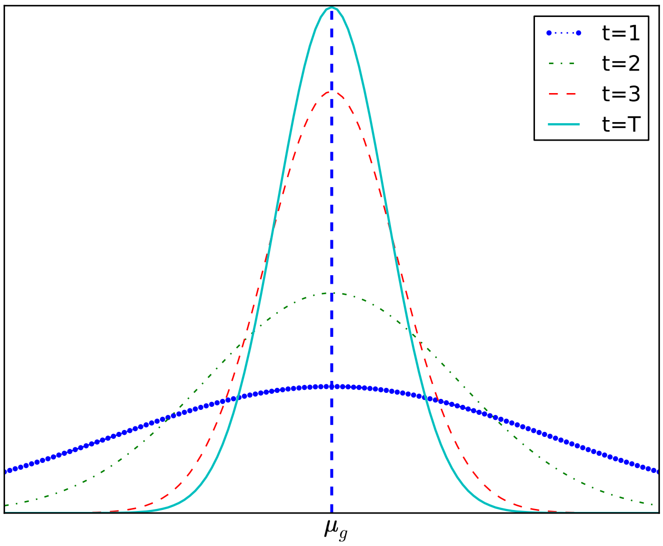

Figure 1: Perceived Variance of GM Profit

belief toward the variance of the GM profit stays the same as it was at time $t-1$. If farmer i experiments the GM seed on part of his or her land at time t, the more he or she plants the GM seeds (increase in G_{it}), the more he or she will learn about μ_g (decrease in σ^2_{igt+1}); And if this farmer lives in a region with high adoption rates of his or her neighbors (increase in G_{-it}), he or she will also have a better knowledge of the GM technology (decrease in σ^2_{igt+1}). However, the information farmer i could get from neighbors may carry additional noise comparing to information obtained from his or her own experience ($|\frac{\partial \sigma^2_{igt+1}}{\partial G_{it}}| > |\frac{\partial \sigma^2_{igt+1}}{\partial G_{-it}}|$). The noise in neighborhood information may come from two sources: 1) some information may get lost during the communication; and 2), if the average GM profit depends on farmers' individual characteristics, as argued by Manski (1993) and Mushi (2004), the information from the neighbors may be biased and not applicable to his or her own case.

For the variance of profit from planting conventional seed, because the conventional seed may be vulnerable to some uncertain events such as pest infestations, we assume its variance depends on a random state variable z_t which follows an AR(1) process. So for farmer i at time t, the variance of the profit from planting conventional seed, σ^2_{ict}, is

$$\begin{aligned} \sigma^2_{ict} &= \sigma^2_{ict}(z_t) \qquad \text{where} \\ z_t &= \lambda\, z_{t-1} + \nu_t \qquad \nu_t \sim N(0, \sigma^2)\,. \end{aligned}$$

To be specific, we assume σ^2_{ict} to be a linear function of z_t

$$\sigma^2_{ict} = \sigma^2_{ict}(z_{it}) = \gamma_0 + \gamma_1 z_t = \gamma_0 + \gamma_1(\lambda z_{t-1} + \nu_t)\,. \tag{4}$$

Assume γ_1 positive, a higher infestation rate brings a higher variance of the profit from the conventional seed, therefore a lower expected utility. It also suggests that if farmer i knows that the value of the random state variable z_t will be very low at time t, then a low enough σ^2_{ict} would lead to a low adoption of GM seed even he or she knows that GM seed is overall better than conventional seed.

2.1.3 Mean Profit

I assume that farmers' beliefs on the mean of the GM profit μ_{igt} to be constant, i.e., farmers receive an unbiased estimator of the mean on perceived profit of GM seed initially, and only update their beliefs on its accuracy (the variance σ^2_{igt}) in the later time periods. [3] Moreover, we assume that there is heterogeneity in farm land and that a farmer can conceptually arrange all his or her lands in such an order that the suitability of the land for planting GM seeds is decreasing. This suitability for GM seeds may be related with soil conditions, land quality, infestation vulnerability, or other factors of the land. Suppose farmer i owns a total of A_i units of land plots, we assume that the difference between the unbiased belief of GM

[3] In reality, farmers may update their beliefs on the mean of the average GM profit too. See Appendix A for the Bayesian updating of the mean. We impose this restriction in order to facilitate my empirical analysis later for the U.S. soybean market. Moreover, my assumption may not be overly restrictive. As some agronomists point out (Hurley, Mitchell, and Rice, 2004), in general the GM technology does not increase but insure the potential yield, therefore GM seed does not necessarily bring a higher revenue.

mean profit and the conventional mean profit for the k^{th} plot, $\Delta\mu_i^k$, is

$$\Delta\mu_i^k = \bar{\mu}_i^k - \eta_c = \eta_{ig}(X_i) - \eta_{gc}\frac{k}{A_i} \qquad \text{where } k = 1, 2, \ldots, A_i.$$

where $\bar{\mu}_i^k$ is farmer i' s belief of GM profit, η_c is the mean profit of the conventional seed, η_{ig} is the highest possible profit difference, which is specified to be a linear function of farmer i's characteristics X_i as $\eta_{ig} = \eta_g + c\,X_i$. And we assume $\eta_{gc} > 0$, i.e., the mean profit difference between GM and conventional seed is decreasing in k.

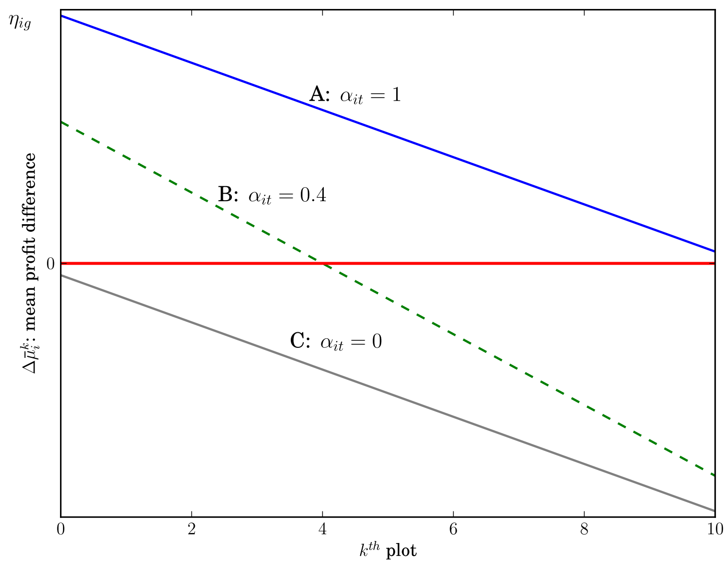

Figure 2: Difference in Mean Profits

If farmers' adoption decisions are made on comparing mean profits only, without forward looking, the optimal adoption rate is then determined by the intercept η_{ig} and the slope η_{gc} of the mean profit difference of conventional seed and GM seed. Figure 2 plots scenarios where the optimal adoption rate α_{it} can be zero (line C: no adoption), 1 (line A: full adoption) or between 0 and 1 (line B: partial adoption).

Suppose farmer i adopted a total of G_{it} plots of GM seed at time t, the total mean profit he or she could get is

$$\begin{aligned} E[\pi_{it}] &= \sum_{k=1}^{G_{it}} \left(\eta_c + \eta_{ig} - \eta_{gc} \frac{k}{A_{it}} \right) + \sum_{k=G_{it}+1}^{A_{it}} (\eta_{c0}) \\ &= \left(\eta_c + \eta_{ig}\alpha_{it} - \frac{1}{2}\eta_{gc}\alpha_{it}^2 \right) A_{it} \end{aligned}$$

where $\alpha_{it} \equiv \frac{G_{it}}{A_i}$, i.e., the adoption rate of GM seeds by farmer i at time t.

2.2 Adoption Process

The problem for farmer i in time t is to choose an adoption rate α_{it} in order to maximize his or her total discounted expected utility. Assume independence between profits from land plots, the total mean and variance of the profit for farmer i at time t is

$$E[\pi_{it}] = \left(\eta_c + \eta_{ig}\alpha_{it} - \frac{1}{2}\eta_{gc}\alpha_{it}^2 \right) A_{it} \tag{5}$$

$$\sigma^2(\pi_{it}) = A_{it}^2 \left(\alpha_{it}^2(\sigma_{igt}^2 + \sigma_\varepsilon^2) + (1-\alpha_{it})^2\sigma_{ict}^2 \right) , \tag{6}$$

where σ_{igt}^2 and σ_{ict}^2 are specified in Equation (3) and (4). The current payoff at time t for farmer i is

$$\begin{aligned} u_{it} &= E[\pi_{it}] - \frac{1}{2}\beta_i\sigma^2(\pi_{it}) \\ &= \left(\eta_c + \eta_{ig}\alpha_{it} - \frac{1}{2}\eta_{gc}\alpha_{it}^2 \right) A_{it} - \frac{1}{2}\beta_i A_{it}^2 \left(\alpha_{it}^2(\sigma_{igt}^2 + \sigma_\varepsilon^2) + (1-\alpha_{it})^2\sigma_{ict}^2 \right) \\ &= u_{it}\left(\alpha_{it}^2, \sigma_{igt}^2\left(G_{it-1}, G_{-it-1} | \sigma_\varepsilon^2, \sigma_\xi^2 \right), \sigma_{ict}^2\left(z_t, \nu_t | \gamma_0, \gamma_1 \right), A_{it} | \eta_c, \eta_{ig}, \eta_{gc}, \beta_i \right) \\ &\equiv u_{it}\left(\alpha_{it}, S_{it} | \Theta \right) , \end{aligned} \tag{7}$$

where S_{it} is the state variable, which includes the current belief of the GM profit variance σ_{igt}^2, the profit variance of conventional seeds σ_{ict}^2, and the total soybean acreage A_{it}. Θ is the parameter space of the model $\Theta \equiv \{\sigma_\varepsilon^2, \sigma_\xi^2, \gamma_0, \gamma_1, \eta_c, \eta_{ig}, \eta_{gc}, \beta_i\}$.

It is commonly observed that the technology diffusion follows a pattern of S-curve, i.e., the new technology spreads at an increasing rate during the early period, then its adoption slows down gradually and eventually maintains at a rather constant level. This adoption pattern also holds for the GM soybean seeds in US: after the introduction of GM soybean seeds in the mid-1990s, it spreads across the U.S. rapidly, but after about 10 years, especially after year 2004, its momentum is lost and the adoption rate becomes flat. Motivated by this fact, we model the dynamic adoption problem as a finite period model, i.e., farmer i chooses a sequence of acts $\{\alpha_{il}\}_{l=t,t+1,\ldots,T}$ to maximize his or her total discounted expected utility from time t to the steady state time period T,

$$V_{it} = \max_{\{\alpha_{il}\}_{l=t}^{T}} E_t \sum_{l=t}^{T} \delta^{T-l} u_{il}(\alpha_{il}). \tag{8}$$

With current payoff defined as in Equation (7), the Bellman Equation is

$$V_{it}(S_{it}) = \max_{\alpha_{it}} \{u_{it}(\alpha_{it}, S_{it} | \Theta) + \delta\, EV_{it+1}(S_{it+1}|S_{it})\}. \tag{9}$$

3 Data

In the empirical application, we apply the model developed in Section 2 to the U.S. soybean market. The soybean market is chosen for two reasons: first, it comprises two technologies, the conventionally bred seed and the GM seed designed to control weed, which fits the theoretical model developed for two technologies in Section 2; second, the adoption of GM soybean seed in the U.S. has been stabilized after year 2004, which justifies the finite period assumption in this model.

The empirical analysis is based on a large, extensive survey data collected by dmrkynetec (hereafter DMR). The DMR data comes from a stratified sample of US soybean farmers surveyed annually. It provides detailed farm-level information on seed purchases, acreage, seed types, and seed prices. We identify a panel of 432 farmers who have been surveyed from 2000 to 2004 out of a total of 11,060 farmers in the DMR data. Figure 3 shows the average adoption rate of GM soybean seeds of these 432 farmers over the five years, and the average adoption rate of GM soybean seeds from the whole DMR data and from USDA NASS data during this time period [4]. The sample average adoption rate follows the same pattern as in both the DMR population and the USDA NASS population. It suggests that farmers in my sample may not differ from farmers in the population in terms of adoption behavior. To avoid the complication caused by farmers' switching between soybean and other crops across years, we focus on farmers with relatively constant soybean acreage over time. [5] After the screening, 348 farmers left in my sample. Figure 4 shows the locations of these 348 farmers. Most of whom are scattered in the Midwest area.

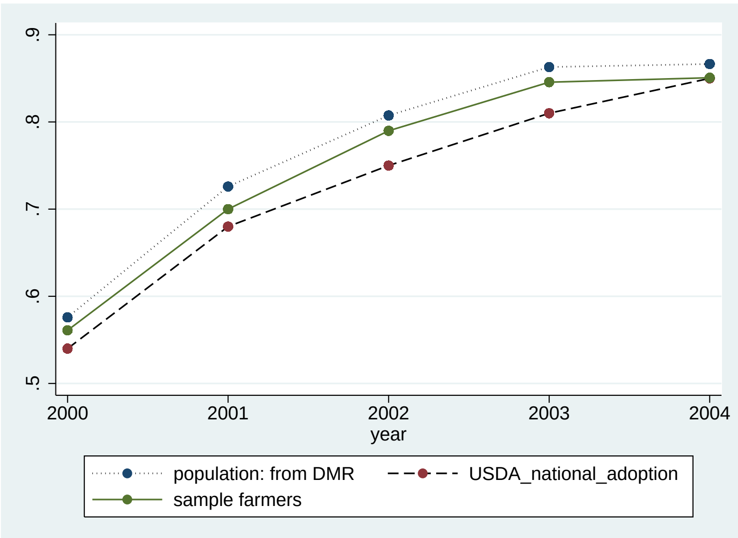

Figure 3: Average Adoption Rates: Sample vs. Population

[4]Data is collected from the website of USDA at http://www.nass.usda.gov/. Please refer to the report on "acreage" from year 2000 to 2004.

[5]In practice we construct a measure which is the standard deviation of the farm size divided by its mean, and we dropped those farmers whose farm size variation is greater than 30%.

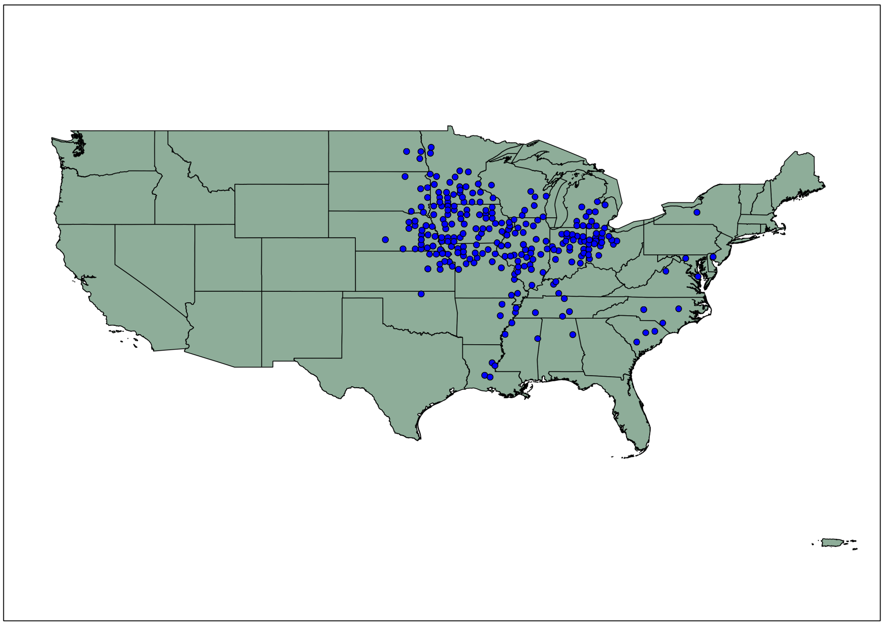

Figure 4: The Location of Selected Farmers

For the neighborhood adoption rate, we define the "neighborhood" at the Crop Report District(CRD) level, and construct the CRD adoption rate using the DMR population data. And we use the average individual soybean acreage and the average CRD soybean acreage over years for A_i and A_{-i} in the empirical analysis. Other farmer characteristics include the latitude and longitude of the center of the county where the sample farms locate.

4 Estimation

In the empirical application, we estimate two models, a myopic model for farmers without forward-looking and a dynamic model in which farmers take account of future benefits or costs when making adoption decisions. For both models, the simulated generalized method of moment (GMM) is used to search the set of parameters that minimize a weighted distance between the predicted adoption path and the observed adoption path.

4.1 Myopic Model

Without forward-looking, farmers only maximize their current payoff in each period. Thus for given time t, farmer i choose the optimal α_{it} to maximize his or her payoff u_{it}, which is defined as in Equation (7), i.e.,

$$\max_{\alpha_{it}} \quad u_{it} = \left(\eta_c + \eta_{ig}\alpha_{it} - \frac{1}{2}\eta_{gc}\alpha_{it}^2\right) A_{it} - \frac{1}{2}\beta_i A_{it}^2 \left(\alpha_{it}^2(\sigma_{igt}^2 + \sigma_\varepsilon^2) + (1-\alpha_{it})^2\sigma_{ict}^2\right).$$

The first order condition gives

$$\alpha_{it}^*(\sigma_{igt}^2|\Theta) = \frac{\eta_{ig} + A_i\beta_i\sigma_{ict}^2}{\eta_{gc} + A_i\beta_i\left(\sigma_{igt}^2 + \sigma_\varepsilon^2 + \sigma_{ict}^2\right)}, \tag{10}$$

where Θ is the parameter space as defined before. And the second order condition is

$$u_{it}^{''} = -\eta_{gc} - A_i\beta_i\left(\sigma_{igt}^2 + \sigma_\varepsilon^2 + \sigma_{ict}^2\right) < 0.$$

Equation (10) suggests that for any set of parameters there is a one-to-one correspondence between σ_{igt}^2 and α_{it}^*. Since the actual adoption rate in the first period (year 2000) is known, we obtain the perceived GM variance for year 2000 σ_{ig0}^2 by solving the inverse function of $\alpha_{it}^*(\sigma_{igt}^2|\Theta)$, which is

$$\sigma_{ig0}^2(\alpha_{i0}|\Theta) = \frac{\eta_{ig} - \eta_{gc}\alpha_{i0} + A_i\beta_i\sigma_{ic0}^2}{A_i\beta_i\alpha_{i0}} - \sigma_\varepsilon^2 - \sigma_{ic0}^2. \tag{11}$$

I then update σ_{igt}^2 for all the following years according to the Bayesian rule in Equation (3), and compute the predicted adoption rate for each farmer in all the following years according to Equation (10).

4.2 Dynamic model

In the dynamic model, farmers will take account of all the future benefits when they are making adoption decisions. In order to compute the predicted adoption path, we make assumptions on the transition probabilities of state variables, value function of the last period and the priors of Bayesian beliefs.

Assumption on transition probability

Since we focus my analysis to those farmers with relatively constant soybean acreage over time, and the data suggest that the total soybean acreage in their neighborhood (CRDs) remains rather stable during my study period, we can rewrite A_{it} as A_i and A_{-it} as A_{-i}. The state variables can be transformed to $S_{it} = \{\alpha_{it-1}, \alpha_{-it-1}, z_t, A_i, A_{-i}\}$ according to the specification of σ^2_{igt} and σ^2_{ict}. So the transition probability of the states is

$$P(S_{it+1}|S_{it}) = P(\alpha_{it}, \alpha_{-it}, z_{it+1}|\alpha_{it-1}, \alpha_{-it-1}, z_{it}) = P(z_{t+1}|z_t)\,,$$

because α_{it} is determined by farmers' maximization behavior and the pair of $\{\alpha_{it}, \alpha_{-it}\}$ is a solution of the *Markov perfect equilibrium* as argued by Foster and Rosenzweig (1995) and Besley and Case (1994). For $P(z_{t+1}|z_t)$, we follow Tauchen (1986) to discretize the space of z_t to 9 equispaced points and compute their transition probabilities. See Appendix B for details.

Assumption on the last period

The data suggests that toward the end of my study period (year 2004), change in adoption rate becomes flatten out (See Figure 3). Indeed most farmers stop adjusting their adoption rate of the GM soybean seeds after three or four years since they start the field experiment with GM seeds. Therefore we assume that in the last period the dynamic learning process is already in steady state, i.e., $EV_{iT+1} = EV_{iT}$ for $T \geq 5$. Therefore the Bellman equation for the last period is

$$EV_{iT} = E \max_{\alpha_{iT}} \{u_{iT} + \delta\, EV_{iT+1}\},$$

and

$$EV_{iT+1} = EV_{iT} = \frac{1}{1-\delta} \max_{\alpha_{iT}} u_{iT} \left(S_{iT} | \Theta\right) .$$

Based on the value of the last year, we compute the value function for all the previous years for each farmer according to the Bellman Equation.

Assumption on the prior of Bayesian beliefs

To update the Bayesian beliefs we need the prior for the first period for each farmer. In the myopic case, we infer the prior belief of each farmer from their adoption rates in year 2000. However, in the dynamic model, the relationship between the Bayesian belief and farmers' adoption rate is no longer a one-to-one correspondence. Therefore, we use the beliefs of year 2000 in the myopic case as starting values for the Bayesian beliefs in the dynamic case. However, there might be a systematic error as the belief for a myopic farmer may be different from a forwarding-looking farmer in 2000. To account for this potential bias, we add a parameter b to all the myopic beliefs in 2000 and use them as the priors for the dynamic case.

Compute the predicted adoption rate

The following algorithm is used to compute the predicted adoption rate:

1. Discretize the state/control space;

The state variables are $S_{it} = \{\alpha_{it-1}, \alpha_{-it-1}, z_{it}, A_i, A_{-i}\}$, and adoption rate α_{it} is the control variable. we discretize all the adoption rates $\alpha_{it}, \alpha_{it-1}, \alpha_{-it-1}$ to be 51 equal-spaced points in $[0, 1]$. For the random state variable z_t, as suggested by Tauchen (1986), we discretize it into 9 equal-spaced points in an interval $[\underline{z}, \bar{z}]$, where $\bar{z} = -\underline{z} = 3\sigma^2$ and they are the lower bound and upper bound of z.

2. Simulate the infestation rate z_t for each period;

   We assume z_t is at its invariant state in the first period, and simulate 9 initial points according to its invariant probability. Then for each initial point we simulate a sequence for the next four years according to its transition probability.

3. Compute the Bayesian beliefs;

   We compute the priors as described and update the Bayesian beliefs according to the updating rule in Equation (3).

4. Compute the value function and the policy function, i.e., the optimal adoption rate under each possible state, of the last period;

5. Compute the value function and the policy function for all the previous years by backward induction according to the Bellman equation in (9);

6. Trace out the adoption path for each farmer based on the policy function.

4.3 Simulated GMM

Given the random state variable z_t, simulated GMM is used to estimate the parameters. For the myopic case, we solve the model for all the simulated states z_t and take the average. For the dynamic case, we compute the optimal adoption path for each simulated z_t and then take the average value. In both cases, we try to find a set of parameters that minimize the weighted distance between the predicted adoption rate and the actual adoption rate.

Define the prediction error as $e(\theta) = \alpha_{it}^*(\theta) - \alpha_{it}^s$, where $\alpha_{it}^*(\theta)$ is the predicted adoption rate, α_{it}^s is actual adoption rate, and let D be all the data available, i.e., $D = \{\alpha_{it},\, \alpha_{-it},\, A_i,\, A_{-i}, X_i\}$. Following Hansen and Singleton (1982), we assume that at the true parameter value θ_0,

$$E(e|D, \theta_0) = 0\,. \tag{12}$$

Then for any function of data D, $T(D)$,

$$E(T(D)e(\theta_0)) = 0\,. \tag{13}$$

This fact is used to construct moments to estimate the parameters by generalized method of moments(GMM). Let k be the dimension of the parameters, and l be the dimension of the moments, $l \geq k$ due to identification requirement. Let $g_i(\theta) \equiv T_i(D)\, e(\theta)$, then the GMM objective function is

$$J(\theta) = n \cdot \bar{g}_n(\theta) \cdot W_n \cdot \bar{g}_n(\theta)\,, \tag{14}$$

where

$$\bar{g}_n(\theta) = \frac{1}{n}\sum_{i=1}^{n} g_i(\theta)\,,$$

and the efficient weight matrix is

$$W_n = \left(\frac{1}{n}\sum_{i=1}^{n} \hat{g}_i\hat{g}_i{}' - \bar{g}_n\bar{g}_n'\right)^{-1}\,,$$

with $\hat{g}_i = \hat{g}_i(\tilde{\theta})$ obtained from a preliminary estimation of θ with $W = I$, where I is the identity matrix. The asymptotic distribution of the estimates $\hat{\theta}$ is

$$\sqrt{n}(\hat{\theta} - \theta) \to N\left(0, (G'\Sigma G)^{-1}\right)\,, \tag{15}$$

where $\Sigma = (E(g_i g_i'))^{-1}$ and $G = E\frac{\partial}{\partial\theta'}g_i(\theta)$.

5 Empirical Results

Both the myopic model and the dynamic model are estimated. According to the discussion in Section 4.3, we chose the following instruments to facilitate the GMM estimation: previous adoption rate of farmer i and his or her neighbors' (α_{it-1} and α_{-it-1}), total soybean acreage A_i and A_{-i}, farm characteristics X_i, i.e., the longitude and latitude , plus the prices of GM and conventional seed from individual farmers and their neighborhoods (average price at CRD level). In total there are 17 moments and 15 parameters for the dynamic model and 14 parameters for the myopic model. The discount factor δ is set to be 0.96 for the dynamic model, following the practice in the literature (e.g. Rust, 1987; Pakes, 1986; Crawford and Shum, 2005). The starting value for the myopic model is chosen based on the result of a non-linear reduced form estimation as in Foster and Rosenweig (1995), and we use the estimated parameter from the myopic model as the starting value for the dynamic model. The Nelder-Mead simplex method is used to minimize the GMM objective function for both models. Results are shown in Table 1. Figure 5 plots the predicted average adoption paths from the myopic model and the dynamic model as well as the observed average adoption path.

Myopic vs. Dynamic

The mean squared error (MSE) of the dynamic model is much smaller than that of the myopic model, implying that overall the predictions from the dynamic model fit the data better, which suggests that soybean farmers in my sample are likely to be forward looking rather than myopic. This result suggests the myopic model underestimates the value of early adoption and therefore predicts lower adoption rates at early years. Figure 5 shows that the

Table 1: Estimation Results

	Myopic Model	Dynamic Model	Initial Values
η_g	0.7911	1.1059	1
η_{gc}	0.421	0.5615	0.5
σ_ε^2	0.3496	0.4413	1
σ_ξ^2	217.5944	32.724	10
β_0	1.3375	1.3961	1
β_1	0.0949	0.1578	0
λ	0.1252	0.1502	0.202
σ^2	0.2571	0.2021	0.236
γ_0	3.6317	4.3158	5
γ_1	0.7002	0.3725	1
c1_lat	-2.9913	-2.9389	-2.148
c2_lat2	2.9658	3.0147	2.506
c3_lon	2.2546	2.6878	1.529
c4_lon2	-0.6557	-0.4542	-0.795
b		0.3208	0
J test	104.629	91.7459	
MSE	1537.4541	91.7992	

predicted adoption rate for year 2001 and 2002 from the myopic model is lower than the observed data.

The parameter b, i.e., the difference of the Bayesian belief towards the profit variance of GM seed between the myopic model and the dynamic model, is positive. It suggests that the initial perceived profit risk of the GM seed is higher in the dynamic model. However, since the dynamic model accounts for the future benefits of early adoption, forward looking behavior still generates higher early adoption rates which are closer to the observed data than the myopic model predicts.

Self learning vs. Learning from neighbors

Table 1 shows that the estimated parameter σ_ξ^2, the noise during learning from neighbors, is larger than the converged profit variance of the GM seed (σ_ε^2), or the base line profit

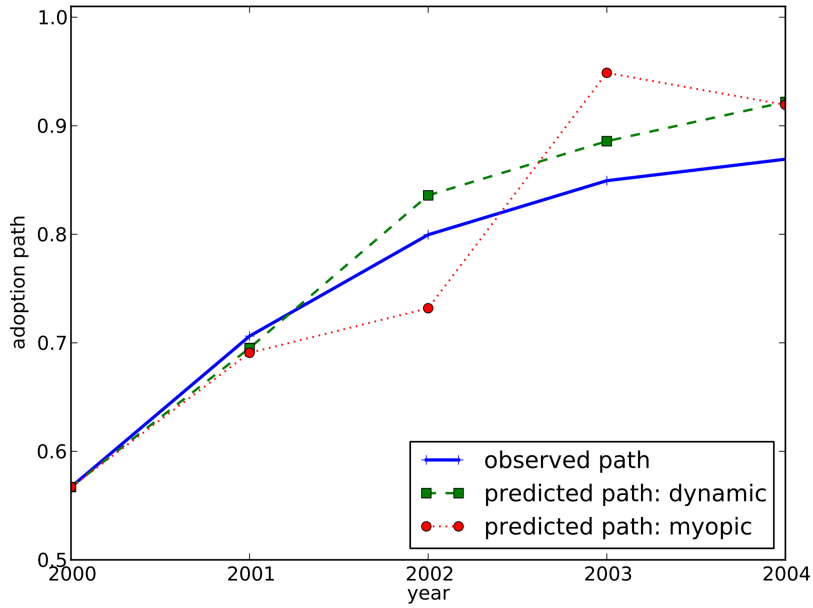

Figure 5: Observed Adoption Path vs. Predicted Adoption Paths

variance of conventional seed (γ_0). It suggests that during the adoption process, farmers rely more on their self experience than the information obtained from from their neighbors' experience. This is consistent with the findings of other related literature (e.g. Munshi, 2004; Baerenklau, 2005; Conley and Udry, 2010).

Mean Profit

Overall, the estimated mean profit parameters (η_g, η_{gc}, and the parameters for latitude and longitude) are consistent with the theoretical model, i.e., the marginal profit from adoption GM soybean seeds is decreasing, with the exact mean profits differ across farms. Comparing to the myopic model, the mean profit from GM seed is higher and with a smaller decreasing marginal profit. This suggests that overall the GM soybean seed is even more profitable if accounting for the future benefit.

The estimated parameters with respect to farm characteristics suggest that the mean profit of GM soybean seed is higher if the farm is located in the south and east area, but with a reversed second order effect in both directions.

Other Results

The estimated parameter γ_1 is much lower in the dynamic model, which implies that comparing to the myopic model, the random state variable z_t has a smaller effect on the profit variance of the conventional seed. This might happen as a forward-looking farmer could neutralize the risk caused by random events across time.

The estimated β_1 is positive, suggesting that farmers with larger total soybean acreage are less risk-averse and more willing to adopt the GM seed. This may be driven by the fact that a farmer with more total soybean acreage has more farm land, which indicates his or her wealth status, and that wealthy people are less risk-averse as commonly observed in literature.

6 Conclusion

As Besley and Case (1993) rightly put: a key factor in modeling the technology adoption is "the extent to which empirical estimation is consistent with an underlying theoretical model of optimization behavior". In this paper we construct a dynamic adoption model which models farmers' learning behavior during the process of adopting a new technology. Using the data from a panel of 348 U.S. soybean farmers, we estimate both a myopic model and a dynamic model for their adoption decision on a newly developed GM soybean seed. The results suggest that the myopic model underestimates the value of early adoption, therefore predicts lower adoption rates at early years. Moreover, the dynamic model fits the data better than the myopic model does, suggesting that farmers in my sample behave more likely to be forward-looking. This finding highlights the importance of estimating an empirical adoption model that is consistent with the underlying decision process. It confirms that the technology adoption process in agriculture is likely to be a dynamic process (Griliches, 1957; Barham et al., 2004).

I also find that farmers learn both from their own experience and from the information they obtain from their neighbors' experience. However, the neighborhood effect we find in this case is much smaller than the self learning effect. This result, as suggested by Mushi (2004), may be because that the GM technology in soybean is sensitive to individual farm characteristics, therefore experience from one farmer is not applicable to others and the true distribution of the return of GM soybean seed can only be learned by farmers' own experience. In reality the social learning mechanism may be much more complicated, so a refined social learning mechanism and access to more information on farmers' communication will certainly enrich the model.

Overall, my empirical results underline the importance of dynamics in estimating the technology adoption. The model could also be applied to other topics where the dynamic setup is essential to the problem, such as pest management or irrigation management.

Appendix

A Bayesian Learning

A.1 Self-learning

Suppose at time 0 a farmer has a *prior* of π_g as $N(\mu_{g0}, \sigma_{g0}^2)$. If he or she only tries GM seed on one plot in time 0 and gets a realized profit π_{g0}, then according to Bayesian rule, the *posterior* $N(\mu_{g1}, \sigma_{g1}^2)$ is updated as

$$\mu_{g1} = \frac{\frac{\pi_{g0}}{\sigma_g^2} + \frac{\mu_{g0}}{\sigma_{g0}^2}}{\frac{1}{\sigma_{g0}^2} + \frac{1}{\sigma_g^2}}$$
$$\sigma_{g1} = \frac{1}{\frac{1}{\sigma_{g0}^2} + \frac{1}{\sigma_g^2}}.$$

If he or she planted GM seeds on G_0 plots at time 0 and get an average profit on each plot as $\bar{\pi}_{g0}$, then

$$\mu_{g1} = \frac{\bar{\pi}_{g0}\frac{G_0}{\sigma_g^2} + \frac{\mu_{g0}}{\sigma_{g0}^2}}{\frac{1}{\sigma_{g0}^2} + \frac{G_0}{\sigma_g^2}}$$
$$\sigma_{g1}^2 = \frac{1}{\frac{1}{\sigma_{g0}^2} + \frac{G_0}{\sigma_g^2}}.$$

So the more plots this farmer tries, the more the weight of the *posterior* mean will goes to $\bar{\pi}_{g0}$, which converges to the true mean θ according to the Law of Large Number as the number of plots goes to infinity.

Following Foster and Rosenzweig (1995), we define $\rho_{g1} = \frac{1}{\sigma_{g1}^2}$ as the precision of his or her perceive posterior mean, and similarly $\rho = \frac{1}{\sigma_{g0}^2}$, $\rho_{g0} = \frac{1}{\sigma_g^2}$, then

$$\rho_{g1} = \rho_g + G_0\, \rho_{g0}.$$

we can see that the more plots he or she tries with GM seeds, the more weights of the precision of his perceived posterior mean shifts to the true precision.

A.2 Learning from neighbors

Suppose a farmer may observe the profits of his or her neighbors, but with an additional noise ξ, whose variance σ_ξ^2 is assumed to be known for all farmers. Suppose the neighbors grow H_0 in average at time 0 and he observed an average profit as $\bar{\pi}_{h0}$ from the neighbors, follow the same logic of learning from himself, we can rewrite the posterior as

$$\mu_{g1} = \frac{\bar{\pi}_{g0}\frac{G_0}{\sigma_g^2} + \bar{\pi}_{h0}\frac{H_0}{\sigma_g^2+\sigma_\xi^2} + \frac{\mu_{g0}}{\sigma_{g0}^2}}{\frac{1}{\sigma_{g0}^2} + \frac{G_0}{\sigma_g^2} + \frac{H_0}{\sigma_g^2+\sigma_\xi^2}}$$

$$\sigma_{g1}^2 = \frac{1}{\frac{1}{\sigma_{g0}^2} + \frac{G_0}{\sigma_g^2} + \frac{H_0}{\sigma_g^2+\sigma_\xi^2}}.$$

So the information from his or her neighborhood will accelerate the process for the posterior mean converging to the true mean. And we can similarly define $\rho_{h0} = \frac{1}{\sigma_g^2+\sigma_\xi^2}$, then

$$\rho_{g1} = \rho_g + G_0\,\rho_{g0} + H_0\,\rho_{h0}.$$

A.3 Bayesian Updating

Notice that after time 0, the posterior $N(\mu_{g1}, \sigma_{g1}^2)$ becomes prior for time 1, and farmers keep updating their beliefs as they did in time 0. So for a typical farmer, the Bayesian updating at time t is

$$\mu_{gt+1} = \frac{\bar{\pi}_{gt}\frac{G_t}{\sigma_g^2} + \bar{\pi}_{ht}\frac{H_t}{\sigma_g^2+\sigma_\xi^2} + \frac{\mu_{gt}}{\sigma_{gt}^2}}{\frac{1}{\sigma_{gt}^2} + \frac{G_t}{\sigma_g^2} + \frac{H_t}{\sigma_g^2+\sigma_\xi^2}}, \tag{16}$$

$$\sigma_{gt+1}^2 = \frac{1}{\frac{1}{\sigma_{gt}^2} + \frac{G_t}{\sigma_g^2} + \frac{H_t}{\sigma_g^2+\sigma_\xi^2}}. \tag{17}$$

B Approximation of an AR(1) process (Tauchen 1986)

For an AR(1) process like

$$z_{t+1} = \lambda\, z_t + \nu_t \qquad \nu_t \sim N(0, \sigma^2)\,,$$

Tauchen (1986) suggests an algorithm to approximate it in the following way.

1. First, discretize the space of z into equal-spaced points in an interval $[\underline{z}, \bar{z}]$, where $\underline{z} = -\bar{z}$ are the lower bound and upper bound of z. Suppose there are N points: $\underline{z} = z^1 < z^2 < \cdots < z^N = \bar{z}$; [6]

2. Suppose the length between two points is w, then the transition probability $P_{ij} = P(z^k | z^j)$ can be computed as

$$P_{ij} = \begin{cases} F\left(\frac{z^1 - \lambda z^j + w/2}{\sigma}\right), \quad k = 1 \\ P(z^k - \frac{w}{2} \leq \lambda z^j + \nu \leq z^k + \frac{w}{2}) = F\left(\frac{z^1 - \lambda z^j + w/2}{\sigma}\right) - F\left(\frac{z^1 - \lambda z^j - w/2}{\sigma}\right), \quad 1 \leq k \leq N-1 \\ 1 - F\left(\frac{z^N - \lambda z^j + w/2}{\sigma}\right), \quad k = N \end{cases}$$

3. Get the invariant probability P^z of each state

   Given the transition probability P, we can compute the invariant probability of each state P^z by a contraction mapping

$$P^z = P P_0^z\,,$$

   where P_0^z is an initial probability of P^z.

[6] Tauchen (1986) suggests that $N = 9$ is adequate for most purposes.

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