Planting Rates in U.S. Maize: Improved Varieties and Learning

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Abstract. Since the advent of hybrids in the 1930's, commercial maize yields have increased at a rate of more than 1.8 bushels per acre per year. Much of these gains have been mediated through increasing plant populations. From 1964 to the present, U.S. corn plant populations more than doubled, from 14,000 to nearly 30,000 plants per acre. In this paper, we use detailed farm-level data to investigate the mechanisms underlying rising planting rates. In particular, we assess whether the positive rate of change in planting rates can be purely explained by breeding improvements to hybrid maize varieties, or whether farmers' observed planting rate choices are also consistent with other factors such as inertia and learning. Through a series of regressions, we estimate how observed corn planting rates change with each additional year of commercial availability. After controlling for both varietal and farm-level heterogeneity, we find that much of the increase in planting rates cannot be explained by a simple diffusion story in which adopters of new varieties immediately jump to the higher economically optimal rate. Rather, we find that farmers tend to plant the same variety at higher rates over time. Through a series of additional regressions, we find that historical based inertia with learning is the most plausible explanation for this observed tendency.

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Introduction

One of the remarkable facts in modern agriculture is the sustained increase in maize yields that followed the diffusion of hybrid varieties in the 1930s. Over the ensuing 80 years, USDA-NASS data show that US maize yields increased more than eight-fold, from roughly 20 bu/acre in the mid-1930s to nearly 175 bu/acre in 2016. Research has found that these yield gains have been the result of a complex interaction between genomic advances due to plant breeding and improved agronomic practices (e.g., pesticide and fertilizer use) (Duvick, 2005). While the exact contribution of each factor remains unclear, there is one unambiguous statistical fact: virtually all observed yield increases have been mediated through increasing plant populations (i.e., plants per acre), rather than increases in yield per plant. For example, from the early 1960s to the present, yields have a little more than doubled (from about 75 bu/acre to 175 bu/acre), while corn plant populations have also roughly doubled (from about 14,000 plants/acre to 29,000 plants/acre). Thus, remarkably, yield *per plant* is only slightly greater now than it was over 50 years ago. This raises an important issue: why have planning rates risen so significantly and what factors have played a role in farmers' planting rate choices? Agronomical research has found that newer maize hybrids possess significantly higher optimal planting rates. Thus, one potential explanation is that over time new varieties with higher optimal rates enter the market and supplant older varieties with lower optimal rates. This raises an additional question, however: do farmers immediately plant new hybrids at their higher optimal rate, or is there a transition period during which they "figure out" the optimal rate?

This paper seeks to understand the mechanisms behind rising planting rates in US maize. We place a particular focus on the possibility of learning as a feature of farmers' planting rate choices. Learning is known to matter in product markets with asymmetric information and high complexity. It has been widely studied in consumer goods markets, particularly as an explanation for purchase behaviors (Dubé, Hitsch and Rossi 2010). Considerably less empirical work on these issues has been conducted in an input decision context. Nonetheless, the choice of planting rates in maize constitutes the type of decision where continuous learning may be present. The US maize seed market is characterized by a large number of differentiated varieties with short commercial life cycles (Magnier, Kalaitzandonakes and Miller 2010). Thus, there is significant scope for continuous learning and experimentation in the face of uncertainty.

To conduct our analysis, we draw on a large, farm-level dataset that spans the period 1995-2011. The dataset contains detailed information on the seed corn purchase decisions of more than 4,700 U.S. farmers per year. Given this information, we investigate the possible sources of increasing planting rates in three steps. First, we estimate regressions in which the planting rate is modeled as function of how many years a commercial variety has been available. Importantly, we have information on both the variety of corn that was planted and the individual that planted it, allowing for the inclusion of variety and farmer fixed effects. Results from these regressions show that planting rates increase substantially with commercial age, even after controlling for varietal heterogeneity, thus providing strong evidence that the increase in planting rates cannot be explained by a simple diffusion story in which new varieties with higher optimal rates supplant old varieties with lower optimal rates. In the second step, we estimate how the variance of planting rates changes with commercial age. We find that the variance of planting rates for particular varieties decreases significantly over time, a finding which is consistent with learning. Learning alone, however, does not necessitate an increasing trend in planting rates, as farmers may both overshoot and undershoot the optimal planting rates. Thus, in a third step, we estimate regressions in which the maximum and minimum planting rates for different varieties are regressed on the commercial age variable. These regressions reveal that the average maximum planting rate slightly *declines* over time, whereas the minimum planting rate increases significantly over time. Taken together, we interpret these findings as providing strong evidence that biased learning – learning in which farmers are more likely to undershoot rather than overshoot the optimal rate – has been a major source of rising planting rates.

The rest of the paper proceeds as follows. First, we provide some important background details on planting rates and discuss the possible sources of rising planting rates. We then describe our empirical approach. This is followed by a detailed description of the data and a discussion of the regression results. We conclude with some implications of our findings, as well as possible avenues for future work.

Background

Plant Population vs. Planting Rate

There is an important distinction between the concepts of "plant population" and "planting rate" (also referred to as the "seeding rate"). The plant population is the number of plants per acre that are standing at the end of the growing season, whereas the planting rate is the number of planted seeds per acre. The concepts are connected by the concept of "stand establishment", which is the percentage of planted seeds that actually germinate and become standing plants. Given information on any two of these variables, one can infer the value of the third variable. For example, if a farmer plants 30,000 seeds per acre and at the end of the growing season the plant population is 28,500, then stand establishment is 95%.

In the empirical section of this paper, we analyze the *planting rate*, and not plant populations. Our conclusions, however, will generally extend to the concept of plant populations given the tight definitional connection between the two. One important issue to note about planting rates is that farmers can substitute higher planting rates for various types of inputs and *vice versa*. For example, in recent years, most seed corn is dressed with a neonicotinoid insecticide. If seed treatments better protect roots from insects, then the germination rate will increase, thus reducing the required seeding rate for a targeted plant population (need source).

Trends in U.S. Maize Planting Rates

Farmers have been steadily increasing planting rates since the commercialization of hybrids in the 1930's (Assefa et al., 2018). From 1964 to 2016, plant populations increased at a rate of about 290 plants per year. This was concomitant with a steady increase in corn yields, which rose at a rate of about 1.82 bu/acre/year during the same time frame (Figure 1).

--Figure 1--

A wealth of agronomical research has demonstrated the close link between maize yield gains and higher planting rates. In a series of experiments, Duvick planted new and old hybrids at different planting rates. He found that at low planting rates, where water stress is not an issue, the yield gains for newer hybrids compared to old hybrids was relatively small. At high planting rates, however, the yield gap between new and old hybrids was substantial (Duvick, 2005). Thus, the primary advantage of modern commercial hybrids is that they can better withstand high stress conditions. Duvick's experiments not only demonstrate the link between yields and plant populations, but they also suggest a likely mechanism for the observed increase in planting rates: over time new varieties that produce higher yields at high populations supplant older varieties with lower optimal planting rates.

--Figure 2--

Figure 2 contains average planting rates for the top 14 corn producing states during the 1995-2011 period. Three important regularities emerge from this figure. First, planting rates have unsurprisingly risen at about the same rate as plant populations during this period: a fitted linear trend indicates that planting rates increased at a rate 272 kernels/acre/year. Second, certain states typically have significantly higher planting rates than others. For example, Minnesota consistently had the highest mean planting rate, whereas states like South Dakota and Kansas had significantly lower rates. This is consistent with the agronomical literature, which has found that the benefits of higher planting rates are limited by precipitation and soil conditions (Assefa et al., 2018). Third, not only does it appear that certain states have consistently lower planting rates, but there also appear to be differences in the trends for each state. Lower production states such as Texas, for example, demonstrate significantly slower rates of increase compared to high production states.

As it concerns our empirical approach, the fact that there are significant differences in planting rates across states suggests that controlling for regional heterogeneity is very important. In addition, our empirical framework should allow for differences between high production and low production states.

Why Have Planting Rates Steadily Increased?

To help understand the potential mechanisms behind rising planting rates, Figure 3 depicts a hypothetical diffusion scenario with four varieties over a seven-year time period (2000-2006). We assume that each variety has a four-year commercial life cycle, and that each variety has a different optimal planting rate.

--Figure 3--

Variety 1, for example, is introduced in the year 2000 and has an optimal planting rate of 24,000 kernels per acre. Over time, new varieties with progressively higher optimal planting rates enter the market and older varieties with lower optimal rates exit the market; by the year 2006, the only variety left is Variety 4, which has an optimal planting rate of 30,000 kernels. The black trend line plots average planting rates over time. It has been constructed under the key assumptions that each of the available varieties are adopted in equal proportions and that farmers immediately and always plant the varieties at their optimal rate (assuming no heterogeneity and no changes in other possibly relevant factors such as seed and output prices). The upwards trend is therefore solely a consequence of the diffusion of new varieties with higher optimal planting rates. Whether this is true in reality is an open question, but irrespective of whether it is, it produces a testable prediction: the within-variety trend (i.e., the estimated trend with variety fixed effects) will have a slope equal to zero (as evidenced by the flat trend lines for each of the four varieties). Moreover, if we allow for optimal planting rates to be heterogeneous among farmers, and we allow for changes in seed and output prices, both realistic assumptions, the prediction remains the same as long as we control for these factors: the within-variety trend will have a slope of zero. Conversely, if we find that the within-variety trend is positive, even after controlling for prices and farmer heterogeneity, then there must be other factors underlying the positive trend. In particular, it must either be the case that optimal rates have changed over time, or if optimal rates have not changed, that there are either adjustment costs or there is uncertainty about optimal rates.

Consider first the possibility that the optimal rates for particular seed varieties have been increasing over time. This could be because seeding technologies have steadily improved, the optimal rates for complementary factors have steadily changed, or some other type of gradual technological improvement that raises the optimal seeding rate. It was already noted, for example, that the use of seed treatments has become widespread. In addition, adoption of no-till has also steadily increased.

Alternatively, it may be the case that the optimal rate for a particular variety doesn't change significantly over time, but farmers' knowledge about the optimal rate does. In a given region there can be hundreds of different varieties available, and the commercial life-cycle for a typical variety is relatively short, usually five years or less (Magnier et al., 2010). Thus, uncertainty plays a major role in farmers' choices of what planting rate to use. Interestingly, learning *per se* does not imply increasing planting rates. The presence of uncertainty can just as well imply that farmers overshoot the optimal planting rate and then correct downwards in the future. Thus, additional assumptions about the underlying production function or about farmer preferences (e.g., risk aversion) are required to explain what may be described as "biased learning".

Empirically, we need to be able extract signals from the data that only indicate learning, and not changes in optimal rates. Of course, both mechanisms may partially hold. It may very well be the case that both learning and improved seeding technology have contributed to rising trends. However, as the evidence bears below, learning seems to have played the most important role in rising trends. To this end, we look at two tendencies in the data that will tend to manifest as a consequence of learning but not improvements in seeding technology. The first is a reduction in the variance of planting rates for specific varieties over time. The second is a difference in the trends of the maximum observed planting rate (for a particular variety) and the minimum observed planting rate. Learning will imply that the variance decreases, and biased learning will imply that the maximum rate increases at a slower rate (possibly decreases) compared to the minimum rate. Improvements in optimal rates, however, imply neither, and thus if we find that both are present, learning is likely to be present.

Methods

We conduct the empirical analysis in three stages. In the first stage, we estimate the following regression equation:

(1) $$s_{ijt} = \alpha \cdot (r_{ijt} / p_t) + \beta \cdot (yr\_since\_intro_{jt}) + \delta' x_{it} + \lambda_{ij} + +\varepsilon_{ijt}$$

where s_{ijt} is the planting rate (kernels/acre) for variety j in year t by farmer i and $\left(r_{ijt} / p_t \right)$ is the ratio of the seed price ($/80,000 kernels) to the corn futures price ($/bu) for variety j in year t by farmer i. The key variable of interest is $yr\_since\_intro_{jt}$, which measures the number of years variety j has been commercially available as of year t. For example, this variable would take on a value of two in the year 2002 for a variety introduced in 2001. The vector x_{it} contains variables for the share of acres planted with no-tillage operations and the share of acres planted with neonicotinoid treated seed.

The term λ_{ij} is a farmer-variety fixed effect. In the results section, we actually provide estimation output for several different levels of fixed effects. In the simplest case, we set $\lambda_{ij} = 0$. In another case, we only allow for varietal heterogeneity: $\lambda_{ij} = \lambda_j$. In another case, still, we model varietal and farmer heterogeneity through additive fixed effects: $\lambda_{ij} = \lambda_i + \varsigma_j$. In total, we report estimation output for six different levels of fixed effects, with the finest level consisting of a separate intercept for each farmer-variety combination (i.e., λ_{ij}). In general, both variety fixed effects and farmer fixed effects are essential for identifying the coefficient on the commercial age variable. For example, if the adoption of new varieties proceeded from high to low density regions over time, then the coefficient would be biased downward. The coefficient will also be biased downward if varieties introduced late in the sample are planted at higher rates (which they are).

The main purpose of this first stage is to test for whether "" is statistically different from zero. If the null is rejected, then an instantaneous adjustment story in which farmers immediately plant new and improved hybrid varieties at their higher optimal rates cannot fully account explain slope of the trend in planting rates.

Planting Rate Variance Regressions

In the second stage, we regress the variance of planting rates for individual varieties on the commercial age variable. If there is learning, we would expect a decrease in variance over time: as farmers learn about the optimal density through observed yields, the distribution of planting rates should cluster more closely around the true optimal value. To investigate this econometrically, the dependent variable of our regression is the standard deviation of planting rates for a particular variety in a given year. Specifically, we estimate

(2) $$sd_{ljt} = \phi \cdot (yr\_since\_intro_{ljt}) + \rho' z_{ljt} + \gamma_l + \kappa_j + u_{ljt}$$

where sd_{jt} is the standard deviation of planting densities for variety j at time t in location l, $yr\_since\_intro_{ljt}$ is the number of years variety j has been available at time t, and γ_{lj} is a variety fixed effect. Unlike the planting rate regressions, these regressions cannot be estimated with farm-level observations because in a given year we observe a farmer's planting rate choice for specific variety at most once (i.e., there will only be one observation). A certain level of aggregation therefore needs to be chosen. We estimate equation (2) for three different aggregation levels: state-year, regional-year (the region is the central corn belt), and national. Learning would be consistent with $\phi < 0$.

Maximum and Minimum Planting Rate Regressions

The variance regressions allow us to test for whether a general type of learning was present, but as noted, the presence of learning doesn't necessitate a positive planting rate trend. Thus, for learning to have played role in rising rates, there needs to have been additional factors present such as risk aversion. To investigate this possibility, we re-estimate equation (1), but with the dependent variable as the maximum and minimum planting rates. Like the variance regressions, this cannot be done at the farm level, so we compute the varietal specific maximum and minimum planting rates at the state-year level. If the coefficient on the commercial age variable is significantly smaller for the maximum planting rate compared to the coefficient for the minimum planting rate, then we interpret this as evidence of "cautious learning".

Data and Results

The empirical analysis relies on detailed farm-level data spanning the period 1995-2011. In particular, we use the corn TraiTrak® dataset developed by GfK Kynetec. The dataset was assembled from annual surveys of randomly sampled US farmers, with the samples designed to be representative at the crop reporting district level. Over the period of analysis, the data contains an average of 4,716 farmers per year. For each sampled farmer, we observe the identities of the varieties planted, prices paid, and the rate at which seeds were planted.

In the original dataset, we observe 342,771 purchase events. In order to estimate the model, we trim the dataset in two ways. First, in some cases a farmer did not report the identity of the variety planted, which is coded as "unknown" in the data. Because we cannot include fixed effects for these observations, we drop them from the dataset, which reduces the sample by 44,555 observations. A second issue is that for varieties observed in the first year of the sample we do not know how many years they had already been commercially available. Thus, we also drop all purchase events with varieties that were first observed in 1995, which further reduces the dataset by 45,533 observations. This issue is also potentially present for varieties first observed in later years, such as 1996 or 1997. For example, a variety observed for the first time in 1996 may have actually been commercially available prior to this year if (by chance) it was not sampled in 1995. Thus, we also considered specifications that further truncate the dataset, but found that the results were not measurably affected. Our finalized dataset consists 252,683 observations across the 1996-2011 period. In some specifications, we also include variables for the share of acres (at the CRD level) that were no-till and for the share of acres (at the CRD level) planted in seed that was dressed with a neonicotinoid insecticide. These variables are only available from 1998-2011 and thus the specifications that include these variables have a further reduced sample size of 241,052.

--Table 1--

Table 1 reports summary statistics for each of the variables used in the finalized sample. The mean overall planting rate was 29,179 seeds per acre. We also disaggregate planting rates by the central Corn Belt (CCB) and the non-CCB, where the CCB encompasses IA, IL, IN, and the southern crop reporting districts in MN and WI. The average planting rate in the CCB was 30,521, which compared to the non-CCB rate of 27,797, was significantly higher. On average, the number of years since the first year of commercial introduction was 1.75, though some varieties were actually observed for the maximum possible value of 15 years. A related variable is the life-cycle of a variety, which measures how many years a variety was commercially available. The average life cycle for a variety was just 4.63 years, a relatively short time span. Seed prices averaged $129.04 per 80,000 kernels, and the corn futures price averaged $3.42; the mean ratio of these prices was $37.68.

--Table 2--

To give context to the regression results, we report national and regional specific planting rate trends for the finalized sample (Table 2). Nationally, seed rates increased at a rate of about 255 seeds per year, which is about 10% of the national average in 1996. The rate in the CCB was considerably higher at about 326 seeds per year, whereas in the non-CCB it was lower at 182 seeds per year.

--Table 3--

Table 3 contains regression results for the baseline model. We report results for six specifications, each differing by the type of fixed effects included. The importance of fixed effects is demonstrated most starkly by comparing column 1, which contains no fixed effects, to column 2, which contains variety fixed effects. In column 1, the coefficient on the price ratio variable is large and significant, contrary to expectations, and the coefficient on the commercial length variable is negative and significant. Both coefficients flip in sign upon introducing variety fixed effects. Intuitively, the estimated coefficient is in part based on comparisons of planting rates for newer varieties, i.e. those with short commercial life spans, to planting rates for older varieties that are still on the market. Consider, for example, the unconditional comparison of the planting rate for a variety released in 2011 to the planting rate for a variety released in 2005. In 2011, the commercial life span of the 2011 variety would be zero and the life span of the 2005 variety would be six. If both varieties were planted at the same rate, the estimator would be zero, despite the fact that the variety introduced in 2005 may have been planted at significantly lower rates in previous years. By contrast, the fixed effects estimator in column 2 is based on within-variety variation.

The final four columns introduce different levels of regional and individual specific effects. In general, they confirm the presence of unobserved factors that are both correlated with seed age and planting rates. Column 3, for example, adds CRD fixed effects in addition to variety fixed effects, which results in a larger estimate for the seed age variable (about 118 kernels compared to 74 kernels). This suggests that newer varieties are first introduced in higher planting rate regions (such as the CCB), and then diffuse to lower planting rate regions. Column 4 replaces CRD fixed effects with farmer fixed effects, which has the effect of increasing the coefficient on seed age even further to a point estimate of more than 224 kernels per year. This indicates that early adopters of new varieties tend to plant at significantly higher rates compared to late adopters.

--Table 4--

Table 4 builds on the results in Table 3 by adding additional controls and allowing the commercial age effect to differ by region. The first two columns add variables for the share of acres (at the CRD level) planted with neonicotinoid treated seeds and the share of acres (at the CRD level) that were no-till. Column 1 uses CRD by variety fixed effects and the second column uses farmer by variety fixed effects. Overall, the coefficients on both variables are consistent with expectations: no-till is associated with higher planting rates and neonicotinoid treated acres are associated with lower rates. However, statistical significance is only estimated for the neonicotinoid variable in the CRD by variety specification. Moreover, the coefficient on the commercial age variable is not measurably affected by the addition of these variables.

Columns 3 and 4 permit the effect of commercial age to be different in the CCB and the non-CCB. The estimated coefficients are significantly different by region, with the CCB coefficient being much larger than the non-CCB coefficient. As noted, this is likely due to poorer soil condition and lower precipitation levels, which not only results in a lower average planting rate but a lower upwards trend as well. One implication of this is that under this mode of technological progress, yields will gradually diverge in the CCB and non-CCB region over time.

Overall, the results from Tables 3 and 4 rule out the possibility that the upwards trend in planting rates is purely, or primarily, due to the diffusion of varieties immediately planted at higher optimal rates, at least in the sense that farmers immediately recognized this and acted accordingly (as, e.g., demonstrated in Figure 3). Rather, particular varieties tend to be planted at significantly higher rates over time, and the estimate for this tendency actually increases upon controlling for locational and individual heterogeneity. The increased prevalence of no-till and neonicotinoid treated seeds can also not explain the conditional upwards trend. Among the possible mechanisms that can explain this finding, learning appears most consistent with the results presented shortly. As noted previously, one general prediction of learning is that as farmers gather information from observed yields, they will get closer to the optimal rate, and thus the variance in planting rates will decrease over time.

--Table 5--

Table 5 presents results for the variance regressions. Recall that a certain level of aggregation needs to be chosen. We report results for three different aggregation levels. Column 1 reports results with the dependent variable – the standard deviation in planting rates – calculated at the state-year level (i.e., an observational unit is a variety-state-year). Column 2 aggregates observations to the regional level (CCB and non-CCB) and column 3 aggregates observations to the national level. In all cases, we include varietal fixed effects. The benefit of the more finely aggregated specifications is that can we also include regional dummies to control for locational heterogeneity. All specifications in Table 5 demonstrate statistically significant evidence of a decline in planting rate variance over time. The results in Column 1, for example, indicates that the standard deviation in planting rates falls by about 55 kernels per ace per year.

An alternative explanation to learning is general technological creep, or an increase in total factor productivity. For example, gradual improvements in seeding technology may have fed through to gradually higher seeding rates. All of these forces would get absorbed by the commercial age coefficient. Given the foregoing results, we consider this an unlikely explanation, at least in terms of importance, for two reasons. First, seeding rates in other crops such as soybeans have actually trended downwards over time. In fact, recent field trials suggest that soybean growers could further benefit from reducing seeding rates (De Bruin and Pederson 2008). Thus, it would need to be the case that general technological improvements that make higher seeding rates more profitable in maize have note made higher seeding rates more profitable in soybeans. Second, overall improvements in seeding technology do not imply a reduction in the variance of planting rates, nor do they imply that maximum rates will evolve differently than minimum rates.

Conclusion

Recall that the unconditional trend in seed planting rates was about 255 kernels per acre increase per year. The estimates for the relationship of commercial age to planting rates, those that control for varietal and spatial heterogeneity, suggest that a large portion of this trend – somewhere between 74 and 230 kernels per year – cannot be explained by the diffusion of technologically superior varieties. Consider the following scenario. Suppose that of the 255 per kernel increase, learning was responsible for 150 kernels. What would happen if all uncertainty were eliminated and thus no learning was necessary? In short, the trend for seeding rates would shift up and rotate downwards. At the individual level, each time a farmer would adopt a new variety with a higher optimal planting rate, they would immediately "jump up" to this new rate and then plant at that rate throughout the variety's commercial life cycle. This would eliminate inefficiencies in the sense that farmers, and society as a whole, would not sacrifice yields during a transition period.

There is continuing interest in understanding the root causes of the amazing technical progress that has characterized modern American agriculture. Our paper contributes unique empirical evidence concerning an important link between improved maize varieties and increased yields: higher planting rates. We find that learning has played a major role in rising planting rate, which suggests scope for additional efficiency gains through extension education. In reducing the cost of trying newer varieties, extension activities might also foster the rollout of better genetic varieties

References

Assefa, Y., Carter, P., Hinds, M., Bhalla, G., Schon, R., Jeschke, M., Paszkiewicz, S., Smith, S. and Ciampitti, I.A., 2018. Analysis of Long Term Study Indicates Both Agronomic Optimal Plant Density and Increase Maize Yield per Plant Contributed to Yield Gain. *Scientific reports*, *8*(1), p.4937.

De Bruin, J.L. and Pedersen, P., 2008. Effect of row spacing and seeding rate on soybean yield. *Agronomy Journal*, *100*(3), pp.704-710.

Duvick, D.N., 2005. The contribution of breeding to yield advances in maize (Zea mays L.). *Advances in agronomy* 86: 83-145.

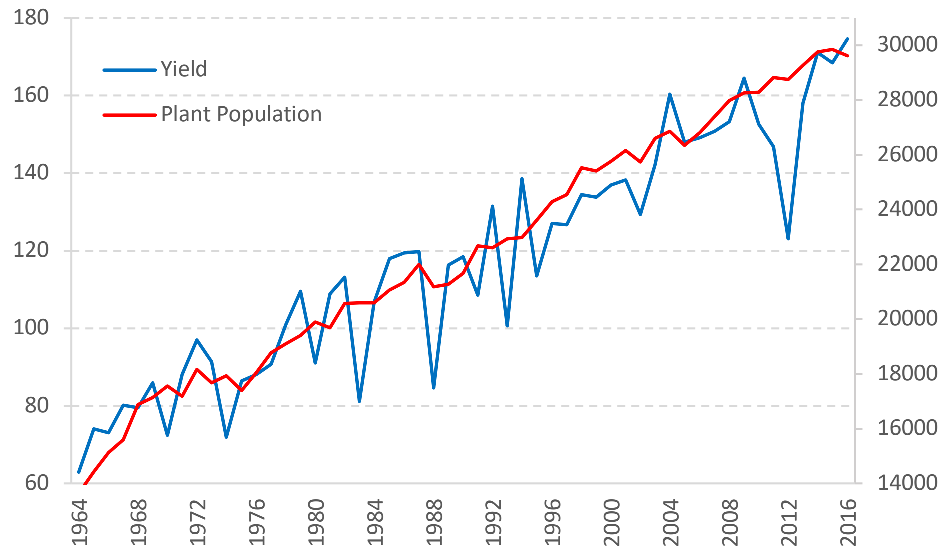
Dubé, J-P., G.J. Hitsch, and P.E. Rossi, 2010. State dependence and alternative explanations for consumer inertia. *The RAND Journal of Economics* 41(3): 417-445.

Magnier, A., N. Kalaitzandonakes, and D.J. Miller, 2010. Product life cycles and innovation in the US seed corn industry. *International food and agribusiness management review* 13(3): 17-36.

Tokatlidis, I.S., and S.D. Koutroubas. 2004. A review of maize hybrids' dependence on high plant populations and its implications for crop yield stability. Field Crop Res. 88:103-114.

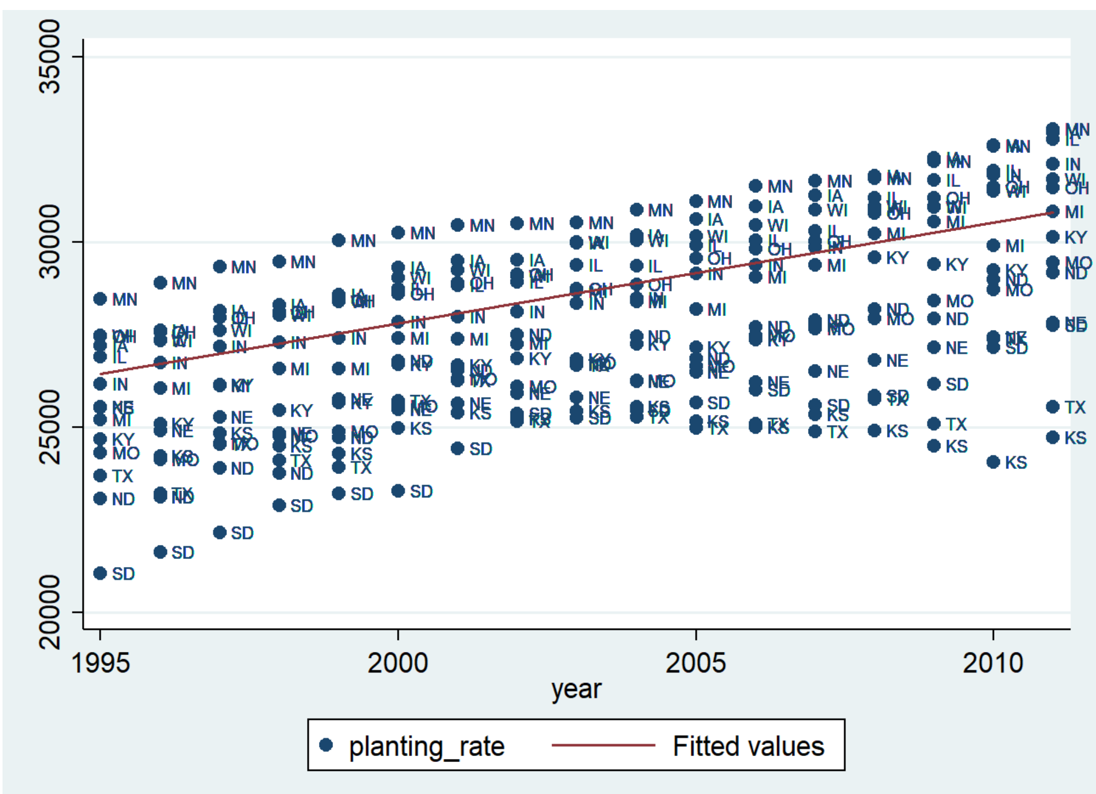
Figures and Tables

Figure 1. U.S. Mean Yield (left, bu/acre) and Plant Population (right, plants/acre): 1964-2016



Note: Plant population data is for the top 8 corn producing states. Source: USDA

Figure 2. Mean Planting Rates by State and Year for the Top 14 Corn Producing States



Note: the equation for the fitted line is: planting_rate = 26,172 + 272*trend. Source: GfK Kyenetec

Figure 3. Hypothetical Diffusion Process for Technologically Superior Varieties

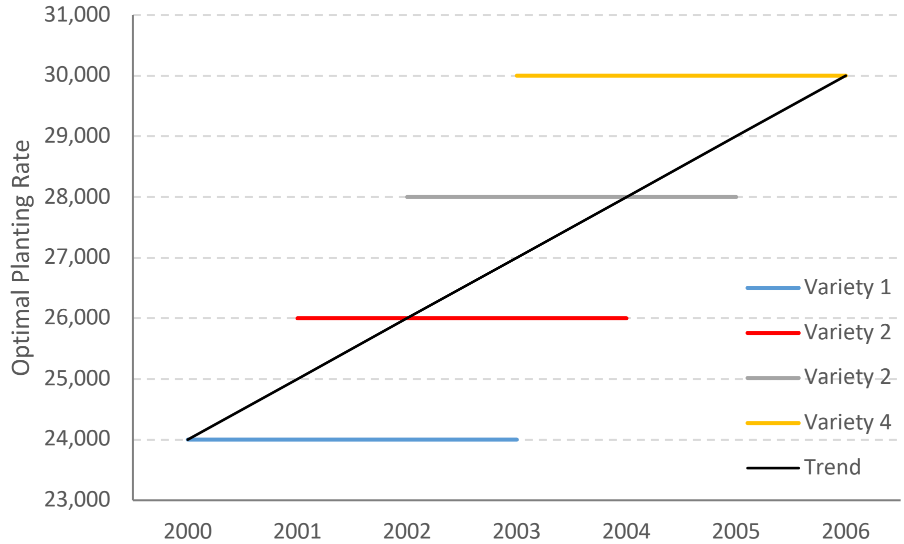


Table 1. Summary Statistics

Variable	N	Mean	S.D.	Min	0.25	Mdn	0.75	Max
Planting Rate (s_{ijt})								
-Overall	252,683	29,179	4,242	8,533	26,667	30,000	32,000	53,333
--CCB*	128,119	30,521	3,259	10,000	28,444	30,968	32,000	53,333
--Non-CCB	124,564	27,797	4,670	8,533	25,000	28,160	31,703	50,667
Years Since Intro	252,683	1.75	1.72	0	0	1	3	15
Life Cycle	252,683	4.63	3.22	0	2	4	7	15
Seed Price	252,683	129.04	59.15	0	87.5	111.16	165.6	390
Corn Futures	252,683	3.42	1.14	2.31	2.47	2.65	4.36	5.68
Price Ratio	252,683	37.68	11.14	0	31.09	36.98	44.3	114.01
No-Till Share	241,083	0.26	0.22	0	0.1	0.2	0.36	1
Neonic Share	241,052	0.45	0.39	0	0	0.5	0.85	1

*IA, IL, IN, and the southern crop reporting districts in MN and WI.

Table 2. National and Regional Trends in Planting Rates

	U.S.	Non-CCB	CCB
Trend[A]	255.04***	181.75***	326.34***
	(1.90)	(3.00)	(1.96)
1996 Mean Planting Rate	26,905.94***	26,183.72***	27,603.29***
	(18.82)	(29.62)	(19.37)
Observations	252,683	124,564	128,119
R^2	0.066	0.029	0.178

[A]The trend in this table is a bit lower than the trend in Figure 2 because the values in Figure 2 are based on the top 14 corn producing states and one additional year of data (1995).

Table 3. Baseline Regression Results (dependent variable is the planting rate)

	(1)	(2)	(3)	(4)	(5)	(6)
Years Since Intro	-73.06***	74.02***	117.56***	224.72***	130.71***	230.03***
	(4.85)	(5.69)	(4.94)	(4.13)	(5.73)	(8.67)
Price Ratio	54.93***	-1.48*	-3.47***	-0.06	-4.29***	-0.26
	(0.75)	(0.90)	(0.78)	(0.63)	(0.89)	(1.42)
Fixed Effects	None	Variety	Variety, CRD	Variety, Farmer	Variety× CRD	Variety× Farmer
Observations	252,683	252,683	252,683	252,683	252,683	252,683
R^2	0.022	0.276	0.463	0.771	0.610	0.835

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4. Additional Results for the Baseline Model (dependent variable is the planting rate)

	(1)	(2)	(3)	(4)
Years Since Intro	141.97***	231.87***		
	(8.16)	(11.20)		
--Non-CCB			91.42***	196.90***
			(9.98)	(14.12)
--CCB			196.09***	269.66***
			(10.22)	(14.56)
Price Ratio	-4.00***	0.28	-4.14***	0.15
	(0.89)	(1.42)	(0.89)	(1.42)
No-Till Share	42.22	54.37	100.62	79.93
	(98.57)	(123.67)	(98.76)	(123.81)
Neonic Share	-155.85**	-61.51	-183.99**	-70.27
	(74.58)	(99.97)	(74.63)	(99.97)
Fixed Effects	Variety× CRD	Variety× Farmer	Variety× CRD	Variety× Farmer
Observations	241,052	241,052	241,052	241,052
R^2	0.612	0.839	0.612	0.839

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5. Results with the Standard Deviation of planting rates as the Dependent Variable

	(1)	(2)	(3)
Years Since Intro	-55.27***	-49.12***	-34.68***
	(7.31)	(7.74)	(8.17)
Price Ratio	-4.59***	-1.45	-1.79
	(1.55)	(1.84)	(2.03)
Aggregation Level	State	CCB	U.S.
Fixed Effects	Variety, State	Variety, CCB	Variety
Observations	36,807	29,818	26,228
R^2	0.278	0.404	0.459

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6. Regression Results for Min and Max Planting Rate Regressions

	Max Planting Rate	Min Planting Rate
Years Since Intro	-38.53***	226.20***
	(7.74)	(8.02)
Price Ratio	-3.79***	-1.64
	(1.42)	(1.44)
Aggregation Level	State	State
Fixed Effects	Variety, State	Variety, State
Observations	106,623	106,180
R^2	0.452	0.452

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$