Kansas Farm Adoption of Embodied Knowledge and Information Intensive Precision Agriculture Technology Bundles

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Introduction

The last twenty years has seen the rapid rise of on-farm adoption of precision agriculture (PA) technologies, however the rate of adoption for specific technologies remains largely unknown. In the fall of 2015, the Kansas Farm Management Association (KFMA) began collecting information regarding member farms' prior and current adoption of PA technologies. Among the technologies asked about were embodied knowledge technologies and information intensive technologies. Embodied knowledge technologies (e.g. automated section control) refer to a group of technologies where no additional skills or training is needed in order to benefit from the value embodied within the technology. Information intensive technologies (e.g. precision soil sampling), on the other hand, refer to a group of technologies that provide large amounts of site-specific data, but require the farmer to gain additional skills or training to receive full value from the data produced. Based on the responses of KFMA member farms, a retrospective panel dataset was constructed showing adoption decisions over time.

Miller et al. (2017) explored this dataset to examine farm adoption of groups ('bundles') of PA technologies over time. However, their analysis was limited to information intensive technologies only. The current study expands on Miller et al. (2017) by adding analysis on embodied knowledge technology adoption and by using a larger sample size ($n = 545$) than was available in the prior Miller et al. (2017) study ($n = 348$). The specific objectives of this study are: (i) identify the individual and groups (i.e. 'bundles') of embodied knowledge technologies and information intensive technologies adopted over time, and (ii) estimate the likelihood of a farm transitioning from one bundle of technology to another.

Literature Review

Previous studies have categorized PA technologies into one of two broad groups, embodied knowledge and information intensive (Fernandez-Cornejo et al. 2001; Griffin et al. 2004). Embodied knowledge technologies encapsulate the group of technologies where the end user does not need to have specialized skills to make full use of the technology (i.e. the value of the technology is 'embodied' within it). Information intensive technologies refer to the group of technologies that generates substantial amounts of data (and possibly information) that can be used in future decision-making, but that the end user must interpret or need to have specialized skills in order to fully explore.

Automated guidance and automated section control are considered embodied knowledge technologies. The latter technology bundle has been adopted at relatively high rates compared to other precision technologies (Erickson and Widmar 2015; Schimmelpfennig 2016), due to their associated reduction in human capital requirements (Fernandez-Cornejo et al. 2001). Global navigation satellite systems (GNSS)-enabled navigation technologies are increasingly being used by commercial applicators and farmers. Automated guidance technology has proven quite popular, being rapidly adopted by service providers since commercialization, with current adoption rates over 80% (Erickson and Widmar 2015). Farm-level trends regarding automated guidance have been similar to the trends seen with service providers; automated guidance was reported to be used on 45% to 55% of planted acres from 2010 to 2013 (Schimmelpfennig 2016). Conversely, adoption of lightbar guidance technology by service providers has ceased expanding (Erickson and Widmar 2015). Currently, embodied knowledge technologies in general, and automated guidance in particular are adopted by more farmers than other technologies.

With respect to information intensive technologies, yield monitors have been considered the benchmark from which to judge adoption of other technologies. By the mid- to late-1990s, yield monitors were the most commonly adopted precision technology (Griffin et al. 2004). Site-specific yield monitor data was feasible once GNSS became available for civilian use in 1994. Across the United States, the percent of acreage covered by harvesters equipped with GNSS yield monitors have steadily increased since the introduction of the technology - especially on corn and soybean acreage (35% and 30%, respectively) (Schimmelpfennig 2016). The rate of adoption on wheat and rice acres however is lower than on corn and soybean acres, but still surpasses adoption rates on cotton and peanut acres.

Data and Descriptive Statistics

The Kansas Farm Management Association (KFMA) is an organization affiliated with Kansas State University that provides farm management and financial planning assistance to over 2334 member farms (as of 2015). Additionally, the KFMA maintains a database that has 44 years of production and cost information for member farms. Starting in the fall of 2015, KFMA economists began asking Kansas farm members in person about their adoption of PA technologies. As of September 2017, 545 farms have responded regarding prior and current technology adoption, a 23% response rate. Technologies asked about included both embodied knowledge (including automated guidance, lightbar, and automated section control) and information intensive (including yield monitor, precision soil sampling) technologies. Based on the responses from the questionnaire, a retrospective panel data set was constructed showing the adoption of different technology bundles over time. In general, adoption of technology on Kansas farms has mirrored national adoption trends, with embodied knowledge technologies having higher rates of adoption than information intensive technologies[1].

[1] Erickson and Widmar (2015) began reporting lightbar and automated guidance services since 1999 and 2004, respectively, by agricultural service providers. Their results show relatively fast adoption rates for the embodied knowledge technologies. Schimmelpfennig (2016) report increased acreage covered by harvesters equipped with yield monitors for various crops and that guidance technologies have been adopted at a faster rate than variable rate technologies.

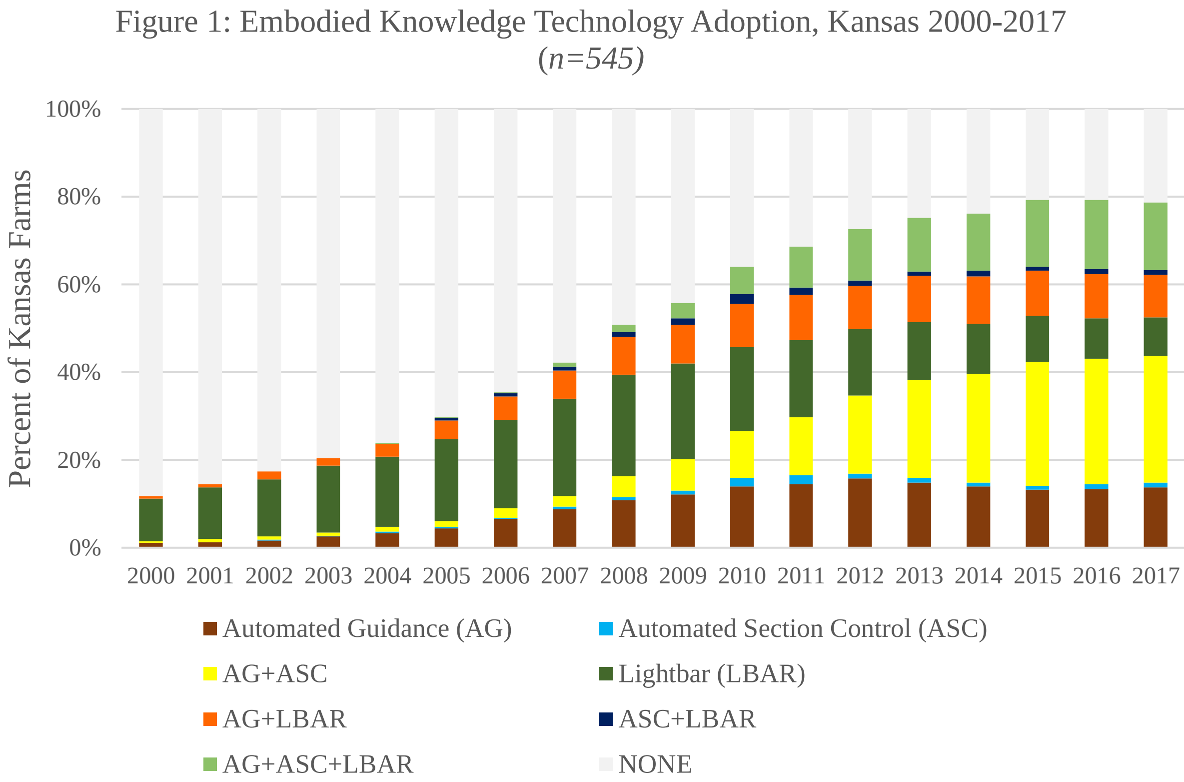

Figure 1 shows the changing trends in the adoption of embodied knowledge technology bundles since 2000. These bundles include one or more of the following technologies: automated guidance (AG), lightbar (LBAR), and automated section control (ASC), as well as a 'none' bundle. Over this time period growth in the farm adoption of these embodied knowledge technologies increased from less than 15% to nearly 80%. Three distinct 'phases' of adoption can be observed. From years 2000 to 2005, the overall adoption of embodied knowledge technologies nearly doubled. The relative popularity of LBAR during this early phase was likely due to its commercial availability earlier than other technologies. This trend helps explain why appreciable gains for both AG alone and technologies bundled with AG see significant gains in adoption starting around 2006. From 2006 to 2012, adoption of AG alone grows steadily as well as adoption of LBAR and AG together. Adoption of these two technology bundles (i.e. AG and AG+LBAR) fueled the overall growth of the adoption of embodied knowledge technologies, as did adoption of another technology bundle, AG+ASC. In contrast the share of farms adopting LBAR alone began to diminish during this period, significantly decreasing by 2017. In the most recent time period, 2013 to 2017, overall growth in adoption of embodied knowledge plateaued, indicating saturation of adoption (i.e. maturity in growth of adoption). What growth that did occur during this time period came mostly from adoption of the AG+ASC technology bundles and adoption of all three technologies simultaneously, likely replacing previously dominant technology bundles.

Figure 2: Information intensive Technology Adoption, Kansas 2000-2017 (*n=545*)

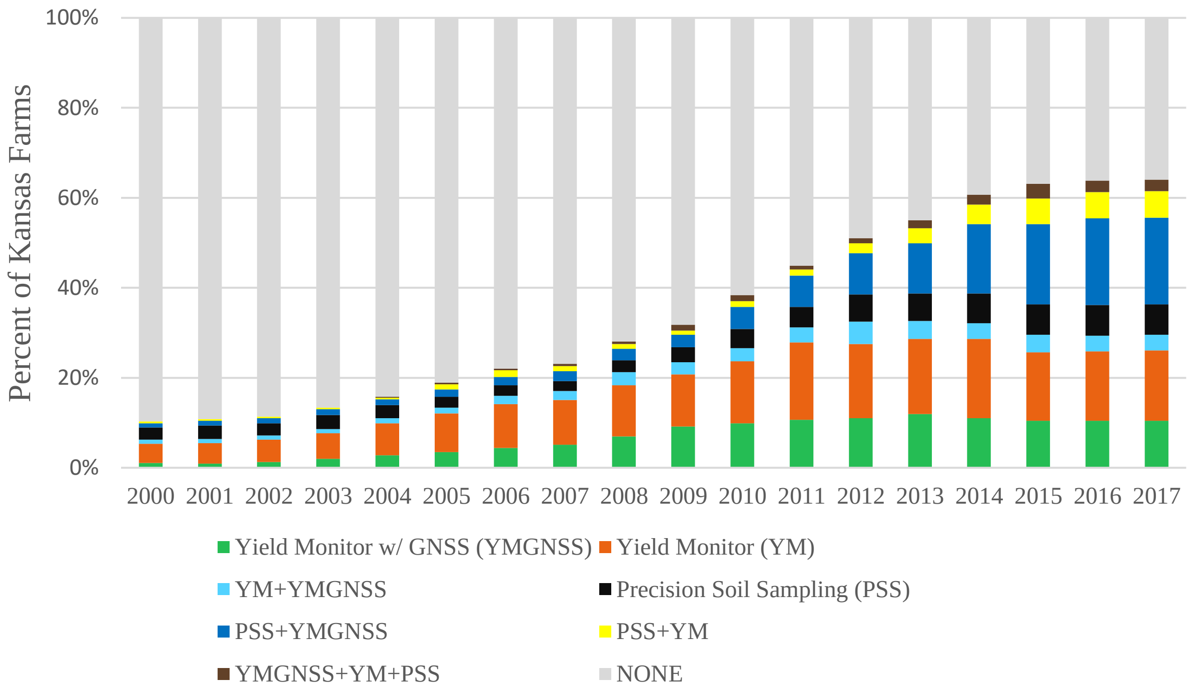

Figure 2 shows the growth in adoption of information intensive technology bundles between 2000 and 2017. Early adoption of information intensive technologies was driven mainly by adoption of yield monitors (YM) without global navigation satellite systems (GNSS). From 2000 to 2005, adoption of YM alone represented nearly 50% of all total information intensive technology adoption. Despite this, overall adoption of these technologies during this initial period was lower than the growth in embodied knowledge technologies. From 2006 to 2014, the overall growth in adoption of information intensive increases dramatically. By 2014, over 60% of all farms have adopted some type of information intensive technology. This was partially driven by continued adoption of YM, as well as adoption of yield monitors with GNSS (YMGNSS), precision soil sampling (PSS), and YMGNSS and PSS together (PSS+YMGNSS). In more recent years (2015 to 2017), as was the case with the embodied knowledge technologies, overall adoption of information intensive technologies by farms has plateaued, with even the bundles remaining at relatively similar levels of adoption. Additionally, amongst adopters (i.e. farms that adopted any bundle other than 'none'), changes from one technology bundle to another one rarely occurred, indicating increased steadfastness in adoption practices across farms.

Adoption Analysis Methods

Markov transition probabilities estimate the likelihood a farm in a given year will adopt a given technology bundle conditional on adoption of a technology bundle in the prior year. Markov transition probabilities were estimated for embodied knowledge and information intensive technologies separately, followed by estimation of Markov transition probabilities for adoption of variable rate technologies jointly with embodied knowledge and information intensive technologies. Markov chain probabilities were estimated using the method of maximum likelihood for the entire sample population using the *markovchain* R package (Spedicato 2017) (R Core Team 2017). The estimated transition probabilities (p_{ij}) follow a one-step Markov chain process, and show the likelihood than an individual farm would remain in (or leave) the state of the world (state *j*) in year $t + 1$, that they inhabited in the previous year (state *i*), *t*. These probabilities are explicitly defined as,

$$p_{ij} = \Pr\{X_t = j | X_{t-1} = i\} \tag{1}$$

The underlying assumption of this probability model is that the state of the world (*j*) that the individual resides in in time period $t + 1$, is a function solely of the state of the world (*i*) that he resided in during time period *t*. The states of the world here represent the PA technology bundles being adopted. Standard errors for each Markov transition probability are estimated following Skuriat-Olechnowska (2005), allowing for asymptotic significance tests using *z*-statistics to determine if transition probabilities are significantly different from zero.

For the embodied knowledge analysis, the eight embodied knowledge technology (including a "no technology adopted") bundles or states are identified in Figure 1. The information intensive analysis estimated transition probabilities for this technology bundle is identified in Figure 2. For both analyses a one-step transition probability matrix (P) examining adoption patterns of technology bundles (states) was estimated for the entire sample for the time period 2013-2016. The matrix P consists of all possible p_{ij} combinations or the i^{th} and j^{th} technology bundles (including both when $i = j$, and $i \neq j$).

Results

This section of the paper presents the two individual analyses, examining the adoption of (i) embodied knowledge technologies and (ii) information intensive technologies

Transition Probabilities - Embodied knowledge Technologies

The results of the estimation of the Markov transition probabilities for the embodied knowledge technology bundles for time period 2013-2016 are shown in Table 1. The majority of the estimated transition probabilities greater than zero were significantly different from zero at a 10 percent level of significance. For the period of study, farmers were more likely to remain within the same embodied knowledge technology bundle from year to year. This persistence in adoption is represented by the large transition probabilities along the diagonal of the *P* matrix in Table 1.

The transition probabilities indicate that the market for PA technology adoption may be saturated, as adoption patterns during the years of observation have by and large not changed (Figure 1). In the case of farmers that had both AG and ASC, this persistent behavior was absolute – the likelihood of remaining with that same technology bundle the following year was 100%. Since the likelihood of persistence for AG+ASC is equal to 100%, this indicates that for farmers adopting this technology bundle, a technology steady-state had been reached. Any transition away from this technology bundle, for this time period, was non-existent.

While the results indicate that persistence is the most likely behavior, movement to new technology categories was also observed. For farmers in certain technology bundles, this movement was largely directed toward adding one new technology. Consider farmers with ASC+LBAR. The likelihood of farmers with ASC & LBAR adopting AG (and moving to the AG+ASC+LBAR category) was 18% in 2013 to 2016 (It is important to mention that often new or used equipment often comes with AG already installed – and adoption of AG may not be the farmer's primary intention). While adding technologies was observed, there were cases of abandonment (albeit quite small levels), as well. Farmers who had adopted AG + ASC + LBAR, had a 1% likelihood of abandoning LBAR technology.

Table 1: Transition Probabilities between Embodied Knowledge Technologies (2013-2016)

	Technology in Current Year							
Technology in Prior Year	**NONE**	**AG**	**ASC**	**AG+ASC**	**LBAR**	**AG+LBAR**	**ASC+LBAR**	**AG+ASC+LBAR**
NONE	0.93*	0.02*	0.01	0.01*	0.02*	0.01	0	0
AG	0	0.90*	0	0.10*	0	0	0	0
ASC	0	0	0.88*	0.06	0	0	0.06	0
AG+ASC	0	0	0	1	0	0	0	0
LBAR	0.01*	0.01	0	0	0.85*	0.07*	0.02*	0.04*
AG+LBAR	0	0.04*	0	0.01	0	0.90*	0	0.05*
ASC+LBAR	0	0	0	0.06	0	0	0.76*	0.18*
AG+ASC+LBAR	0	0	0	0.01*	0	0	0	0.99*

* Significant at the 0.10 probability level

Transition Probabilities - Information Intensive Technologies

The results of the estimation of the transition probabilities for the information intensive technology bundles for time period 2013-2016 are shown in Table 2. The majority of the estimated transition probabilities greater than zero were significantly different from zero at a 10 percent level of significance. Farms with these technologies showed a high degree of persistence of remaining with the same technology bundle over the years of observation. Farms with YMGNSS+PSS had the largest likelihood of persistence - with a 99% probability of remaining with this technology bundle. Farms with YM+YMGNSS had the lowest likelihood of persistence – with an 81% probability of remaining with YM+YMGNSS. It is likely that complementarities between YM and PSS with GNSS drive the adoption of the YMGNSS + PSS technology bundle.

The relatively low levels of persistence for farms with bundles that included both YM and YMGNSS conforms to expectations regarding YM and YMGNSS use. YMGNSS represents an upgrade to conventional YM technologies, therefore gradual replacement of YM with YMGNSS is more likely to be encountered than the purposely planned bundling of the two technologies. An example of this is a farm that buys a new combine equipped with YMGNSS while still using old combines equipped with only YM. This type of behavior is most likely a short-term response to the standardization of YMGNSS on new combines. It is confirmed empirically by the relatively large transition probabilities away from adoption of both YM and YMGNSS to adoption of YMGNSS alone, for the observed time period. Examining Figure 2, one can see that other bundled technologies (i.e. PSS+YM; PSS+YMGNSS) have grown over time, while the bundles where both YM and YMGNSS are present have remained relatively stagnant. The fact that there exist bundles of YM and YMGNSS together may be indicative of farmers' decision or strategy to not upgrade or replace all their equipment at once.

Table 2: Transition Probabilities between Information Intensive Technologies (2013-2016)

Technology in Prior Year	*Technology in Current Year*							
	NONE	**YMGNSS**	**YM**	**YM+ YMGNSS**	**PSS**	**YMGNSS + PSS**	**YM+PSS**	**YMGNSS+ YM+PSS**
NONE	0.92*	0.02*	0.03*	0	0.03*	0	0	0
YMGNSS	0	0.82*	0	0	0	0.18*	0	0
YM	0	0.01*	0.90*	0.03*	0	0	0.05*	0.01*
YM+YMGNSS	0	0.13*	0.01	0.81*	0	0	0	0.05*
PSS	0.01	0	0	0	0.89*	0.05*	0.03*	0.02*
YMGNSS+PSS	0	0	0	0	0	0.99*	0	0.01
YM+PSS	0	0	0.03*	0	0	0	0.97*	0
YMGNSS+YM+ PSS	0	0	0	0.02	0	0.15*	0	0.83*

* Significant at the 0.10 probability level

Conclusion

The purpose of this paper was to examine the adoption of embodied knowledge and information intensive technologies on Kansas farms. Data was collected from farmers in Kansas who are members of KFMA. Two separate analyses estimated Markov transition probabilities to examine the adoption of individual bundles of embodied knowledge technologies and the adoption of individual bundles of information intensive technologies.

Findings suggest that adoption of PA technologies is a long-term and slow process, as the largest transition probabilities for embodied knowledge and information intensive technology bundles was to stay with their current technology bundle. That is, farmers tended to stay with their current technology bundle rather than adopting new technologies. This persistence may be due to a number of factors including risk aversion, high production and investment costs, market availability of services and sequential adoption patterns (Erickson and Widmar 2015; Pannell et al. 2006; Schimmelpfennig and Ebel 2016). In addition, descriptive statistics and the transition probabilities suggest that in the time period examined - market saturation may have been reached, for both embodied knowledge and information intensive technology adoption. That is, farmers adopting embodied knowledge and information intensive technology bundles were much more likely to stay with these bundles than transition to a new bundle in the more recent years. Erickson and Widmar (2015) find this may partially be due to perceptions about PA benefits, applicability of PA technologies to an individual farming operation, variable farm incomes, and land heterogeneity. As technologies became outdated or new technologies became more widely available however, over time, older technologies were abandoned, such as LBAR for AG and YM for YMGNSS. Future research should examine the agronomic, environmental, economic and social factors that impact these transition probabilities to be able to help identify adoption and policy pathways to further improve PA technology adoption.

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