Measuring the Household Impacts of Automated Production in U.S. Agriculture: Evidence from Auto-Steer*

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August 17, 2026

Abstract

This paper develops and estimates a structural model of farm household decision-making to evaluate the economic effects of precision agriculture automation, specifically the adoption of GPS-guided autosteer technology, on U.S. farm households. The model explicitly incorporates automation-enabled multitasking in a household production framework, capturing how autosteer frees operator time and shifts labor allocation across farm work, off-farm work, and leisure. We estimate the model using a unique dataset combining detailed U.S. farm-level production and income records from USDA's Agricultural Resource Management Survey, microdata on multitasking from the 2014–2015 UK Time Use Survey, and the 2025 Iowa Farm and Rural Life Poll. Our empirical results indicate that autosteer adoption has small but significant effects on farm household income, resulting primarily from direct on-farm productivity gains and lower input expenses, although automation also frees up time for additional productive activities (such as off-farm employment or enhanced farm management). These findings suggest that some of the technology's economic benefit comes from improved labor allocation efficiency and flexibility, channels that have been underexplored in the literature on digital agriculture. The results also underscore the broader implications of automation for rural household welfare, highlighting that automation technologies, in certain contexts, can enhance farm family income and labor productivity. By demonstrating the multitasking benefits from autosteer, the study offers a methodological contribution to modeling technological change in household production and provides insights for policies that encourage the adoption of labor-saving technologies in agriculture.

Keywords: Automation, digital agriculture, multi-tasking, autosteer, household production, labor productivity

JEL Codes: Q16, Q12, J43

*We thank seminar participants at the University of British Columbia and the U.S. Department of Agriculture (USDA) for feedback. We also thank J Arbuckle, Katherine Lim, James MacDonald, Peter Orazem, Zachary Raff, and conference attendees at the European Conference on Precision Agriculture for helpful comments. The views expressed in this paper are those of the authors and do not necessarily represent the views or policies of the USDA. This work did not receive extramural funding, and the authors have no financial interests in application of this research, which was supported by the intramural research program of the USDA-Economic Research Service.

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1 Introduction

Interest in the economics of automation has increased rapidly over the past decade, driven partly by major technological advances in global manufacturing, services, and retail sectors (Restrepo, 2024). Automation in these industries has reduced variable costs and increased productivity by streamlining operations; comparable scenarios are taking root in agriculture. Farmers benefit from precision agriculture automation technology (PAAT) through efficiency gains, enhanced well-being, and improved farm sustainability (Campi et al., 2024; McFadden et al., 2024).

However, the benefits and costs of PAAT adoption on commercial farms remain underexplored, particularly regarding their complex effects on farmer time allocation and household income. Early studies on navigation technologies applied partial budgeting and linear programming models, finding that light bar and auto-guidance technologies were profitable only under certain assumptions about technology capacities and farm operations (Griffin et al., 2005; Shockley et al., 2011). More recently, Lowenberg-DeBoer et al. (2021) show that fully autonomous equipment in UK arable crop production allows medium-size farms to approach minimum production costs per unit. However, using data from Dutch dairy farms, Bijl et al. (2007) and Steeneveld et al. (2012) do not find significant economic differences between adopters and non-adopters of automated milking systems. While these studies are valuable and informative, they rely on small samples and omit broader relationships between PAAT adoption, labor supply, and farm household income. The complexity of agricultural automation extends beyond simple productivity gains to encompass fundamental changes in how farmers allocate their time across productive activities, leisure, and household responsibilities; these are relationships that remain underexplored within the existing studies.

The goal of our paper is to develop and estimate a structural model of farm household decision-making that incorporates automation-enabled multitasking to better understand how precision agriculture technologies affect both productivity and time allocation. We seek to answer three key questions: (1) How does autosteer technology affect farmers' ability to multitask and reallocate time between farm work, household production, and leisure? (2) What are the quantitative impacts of automation on farm household income through direct productivity effects and indirect time allocation effects? (3) How do these automation effects on farm household income relate to changes in input costs and time allocations for farm and off-farm work?

Our paper combines detailed time-use survey data from the UK (i.e., the UK Time Use Survey) and the 2025 Iowa Farm and Rural Life Poll with comprehensive farm-level data from the USDA's Agricultural Resource Management Survey (ARMS), to structurally estimate a household production model that explicitly incorporates automation-enabled multitasking. Unlike previous studies that focus solely on farm-level productivity measures, we develop a theoretical framework that captures how automation technologies change the nature of agricultural work by enabling farmers to simultaneously engage in multiple activities, from watching Netflix while plowing fields (Bunge, 2019) to managing other farm or household responsibilities during automated operations. Our empirical approach leverages variation in autosteer adoption and detailed time-diary data to identify key parameters that govern the substitution between sole-tasking and multitasking, the degree of

automation, and elasticities of substitution between different time uses. This combination of rich data sources and structural modeling allows us to quantify not only the direct productivity effects of automation but also the previously unmeasured welfare effects from improved time allocation flexibility.

Our research sits at the intersection of four distinct but interrelated literatures, each of which has examined related phenomena but none of which has captured the full complexity of automation's effects on agricultural households. The first literature examines the economic impacts of automation, particularly those on occupations that are manual-labor-intensive. Recent work by Acemoglu (2025), Acemoglu et al. (2024), and Autor et al. (2024) has established theoretical frameworks for understanding how automation displaces and reinstates labor across different task types, while empirical studies like Aum and Shin (2025) and Cortés et al. (2024) have documented differential impacts across demographic groups. This literature, however, has primarily focused on manufacturing and service sectors, with limited attention to agriculture where the relationship between worker and technology often involves supervision and coordination rather than direct displacement. Our contribution extends this framework to agricultural automation, where farmers become "supervisors of automated equipment" rather than being replaced by it.

The second literature encompasses household and agricultural household production models, building on seminal work by Rosenzweig and Schultz (1983), Huffman (2001), and Taylor and Adelman (2003). Studies like Chavas et al. (2005) and Key and Roberts (2009) have developed increasingly sophisticated models of how farm households allocate labor between on-farm and off-farm activities while accounting for the nonpecuniary benefits of farming. However, this literature has not incorporated how technological change, particularly automation, fundamentally alters the production function and time allocation possibilities within the household. Our model advances this literature by explicitly modeling how automation technologies change the relationship between time inputs and agricultural outputs, allowing for simultaneous engagement in multiple activities that were previously incompatible.

The third literature focuses on multitasking and optimal time allocation between labor and leisure, though this work has developed along two separate tracks that our study uniquely bridges. Workplace (or work-related) multitasking studies like Buser and Peter (2012) and Kim et al. (2022) examine how individuals divide attention across competing work tasks but do not incorporate leisure or household production decisions. Household multitasking research (Kalenkoski and Foster, 2016, 2015) focuses on the relative productivity of multitasking versus sole-tasking in household production but excludes market work considerations. As Zaiceva (2023) notes, the economic literature on multitasking in the household is relatively scarce compared to workplace studies. The agricultural context provides a well-suited opportunity to observe both types of multitasking within a single setting, allowing us to model how automation enables farmers to simultaneously engage in market work (supervising automated field operations) and household activities (managing family responsibilities or consuming leisure).

The fourth literature examines the development effects of increasingly digitalized agriculture,

with recent comprehensive reviews by Khanna et al. (2024) and Lowenberg-DeBoer (2022) highlighting the potential for digital automation solutions to reduce labor gaps while generating new opportunities and improving sustainability. Studies of specific technologies like autosteer (D'Antoni et al., 2012; Al-Amin et al., 2023) have documented adoption patterns and immediate productivity effects, while research on autonomous systems (Al-Amin et al., 2024; Martin et al., 2022) has begun to explore broader implications for farm structure and work organization. This literature has largely focused on technical feasibility and adoption patterns rather than developing formal economic models that can quantify welfare effects and policy implications. Our structural approach enables us to move beyond descriptive analyses to provide quantitative estimates of the economic returns to automation adoption and their underlying mechanisms.

These four strands of literature, while individually well-developed, have not been connected to provide a more integrated evaluation of how automation affects agricultural households' complex decision-making processes. The agricultural context is particularly suited for this synthesis because farming households operate at the intersection of market production and household production, face seasonal labor demands that create scope for multitasking during less intensive periods, and increasingly adopt technologies that transform the nature of agricultural work from direct manual labor to technology supervision and coordination. By developing a unified framework that incorporates insights from automation economics, household production theory, multitasking research, and agricultural technology adoption, we provide new insights on how precision agriculture automation affects both productivity and welfare through its effects on time allocation flexibility. This synthesis enables us to move beyond the partial equilibrium analyses that have characterized previous research to provide a more complete understanding of automation's economic impacts and their policy implications.

2 Model

In line with the literature on the economics of the household, we model a farmer whose utility depends on household consumption and leisure. Productivity and time use enter household utility through consumption (both directly and indirectly), while leisure is the sum of time not allocated to work activities.

2.1 Automation Parameterization

Technological automation enters the model via a continuous parameter $\alpha \in [0, 1]$, where $\alpha = 0$ indicates fully manual work and $\alpha = 1$ indicates full automation. Specifically,

$$\text{Automation continuum} = \begin{cases} \alpha = 0 & \Rightarrow \text{manual task} \\ \alpha \in (0, 1) & \Rightarrow \text{partially automated} \\ \alpha = 1 & \Rightarrow \text{fully autonomous} \end{cases}$$

Table 1 provides simple examples of how α relates to technology for select agricultural activities. For instance, $\alpha = 0$ describes manual operation of farming equipment, hand harvest of specialty crops, or manual milking of dairy cows. By contrast, $\alpha = 1$ describes fully automated operations, such as autonomous equipment in grain production (e.g., recently commercialized driverless tractors) and robotic milking. Of particular interest are interior cases, $\alpha \in (0, 1)$, including farmworkers' use of harvest aids and GPS-based autosteering systems. We focus on the latter technology as an ideal case study given its sharp increase in adoption since the early 2000s, potential for labor-saving benefits, and the clear designation as a partial automation technology.

Table 1: Examples of Automation Continuum

	No automation	Partial automation	Full automation
Example	$\alpha = 0$	$\alpha \in (0, 1)$	$\alpha = 1$
Field crops	Manual guidance	Automated steering	Driverless steering
Specialty crops	Hand harvest	Harvest-assist machinery	Autonomous harvesting
Livestock (dairy)	Manual (hand) milking	Robotic milking	Autonomous robotic milking

We assume that time spent on an automatable task, steering hours (S) in our case, is a major input into production. Use of auto-steer technology provides the farmer with αS units of "multi-tasking" time in the cab. This time may be used for work (e.g., checking weather forecasts or market conditions, answering emails) or leisure (e.g., watching videos). Work that is done during the gained multitasking time reduces work time needed outside the cab, while multi-tasking leisure adds to total leisure. The model accounts for the fact that multi-tasking, whether for work or leisure, may not provide the same level of productivity or utility as dedicated time spent on these activities outside the cab. To capture this nuance in marginal time benefits, we scale multi-tasked work and leisure time by parameters $\beta \in (0, 1)$ and $\phi \in (0, 1)$, respectively. The parameter β essentially represents the marginal rate of substitution (MRS) between multi-tasked and dedicated work time.

2.2 Farm Household Utility Maximization

We assume that farm household utility is a CES function of consumption (C) and total leisure, $H_{tot}^{leisure}$, which itself consists of dedicated leisure time (HL) and multi-tasked leisure time ϕNW, which is afforded by the partial automation technology (auto-steer). Dedicated leisure is conceptualized as time spent on non-work tasks not afforded by the automation technology (e.g., outside of the equipment's cab). The utility weight, $\delta \in (0, 1)$, captures the relative importance of consumption in household well-being. The utility function is:

$$U(C, H_{tot}^{leisure}) \equiv \left(\delta C^{\eta} + (1 - \delta) H_{tot}^{leisure^{\eta}}\right)^{\frac{\psi}{\eta}}, \tag{1}$$

where ψ is the degree of homogeneity, and $\eta < 1$ is the substitution parameter relating to the substitution elasticity, $\frac{1}{1-\eta}$. Total leisured is described by:

$$H_{tot}^{leisure} = HL + \phi NW. \tag{2}$$

Household income is equal to the sum of (1) profit from the farm operation, (2) off-farm work, and (3) an initial endowment of V. Income is spent on consumer goods (C) and savings (B). Off-farm income is equal to off-farm wages (R_H) multiplied by the hours spent on off-farm work (H_{off}). Denoting output price as P, profit from the farm operation is total revenues ($P \times Q$) less total expenses, $\tau R_Z Z$, where $\tau \in (0, 1]$ is the reduction in variable input expense due to automation (e.g., reduced seed, fuel, fertilizer, chemical costs), R_Z is the variable input price, and Z is the quantity of the variable input. For simplicity, we assume that the reduction in variable input expenses induced by automation is a constant cost mark-down, $\tau = (1 - I[\alpha > 0] \cdot c)$. Thus, the household income constraint is:

$$C = PQ - \tau R_Z Z + R_H H_{off} + V - B. \tag{3}$$

Farm output is the result of a CES production function defined over four inputs. Apart from time spent on an automatable task, the farmer dedicates time to non-automatable (or not currently automated) tasks, L_i. However, time that is freed up by automation (W_i) can be re-invested in these tasks, though not necessarily in a one-to-one manner. Thus, the total amount of time spent on non-automatable task i is $(L_i + \beta W_i)$. The variable input (Z) and a fixed level of capital (K) also contribute to total output. The production function is therefore:

$$Q = A\left(\theta_1 S^\rho + \sum_{i=1}^{I} \theta_{2,i}(L_i + \beta W_i)^\rho + \ \theta_3 Z^\rho + \theta_4 K^\rho\right)^{\frac{\gamma}{\rho}}, \tag{4}$$

in which $A > 0$ represents total factor productivity, $\theta_j \in [0, 1]$ for $j \in \{1, \ldots, 4\}$ are the input share parameters with $\sum_{j=1}^{4} \theta_j = 1$, I is the total number of non-automatable tasks, γ is the degree of homogeneity of production, and $\rho < 1$ is the parameter characterizing the elasticity of substitution between inputs, $\frac{1}{1-\rho}$.

The farm household maximizes utility subject to the income constraint and two other constraints. The first is a standard time constraint:

$$S + \sum_{i=1}^{I} L_i \ + H_{off} + HL \leq \bar{T}, \tag{5}$$

where $\bar{T}$ is the total amount of time in hours during the growing season.[1] The second constraint relates to multi-tasked time, dictating that the sum of (multi-tasked) hours spent on work tasks (W_i) for $i \in \{1, \ldots, I\}$ and non-work hours (NW) cannot exceed the total amount of time in which multi-tasking can take place, αS. That is,

[1] It is not strictly necessary to limit the total time, $\bar{T}$, to the number of hours in each (crop) farm household's growing season, although it helps ensure commensurability in scale with the on-farm work hours, S and $(L_i + \beta W_i)$.

$$\sum_{i=1}^{I} W_i \ + NW \ \leq \alpha S. \tag{6}$$

With complete automation, $\alpha = 1$, the entire amount of time that would have been spent on S can be reallocated to a combination of $\sum_{i=1}^{I} W_i$ and NW. Alternatively, as the amount of automation goes to zero, such that all farm work performed is manual, $\sum_{i=1}^{I} W_i \ + NW \ \approx 0$, and equation (6) drops away.

For tractability in the empirical analysis, we aggregate time spent on all non-automated tasks into a single variable $L \equiv \sum_{i=1}^{I} L_i$. The farm household maximizes utility subject to the technology represented in equation (4), its income constraint shown in equation (3), the time constraint in equation (5) and the multi-tasking constraint in equation (6). We also assume a certain degree of automation exists, $\alpha \in (0, 1)$, that K is fixed, and that Z is determined exogenously by the household following recommended input rates (e.g., agronomic nutrient application rates, pesticide label rates) given exogenous farmland quality. The farm household thus optimally chooses among $\{S, L, W, NW, HL\}$.[2] Substituting equations (4) into (3), and then (3) and (2) into (1) yields the following Lagrangian:

$$\begin{aligned}\mathcal{L} = \Bigg(& \delta\Big(P \cdot A\Big(\theta_1 S^{\rho} + \theta_2 (L + \beta W)^{\rho} + \theta_3 Z^{\rho} + \theta_4 K^{\rho}\Big)^{\frac{\gamma}{\rho}} - \tau R_Z Z + R_H H_{off} + V - B\Big)^{\eta} \\ & + (1 - \delta)\ (HL + \phi NW)^{\eta}\Bigg)^{\frac{\psi}{\eta}} + \lambda_1 \left[\bar{T} - S - L - H_{off} - HL\right] + \lambda_2 \left[\alpha S - W - NW\right],\end{aligned} \tag{7}$$

where $\{\lambda_1, \lambda_2\}$ are the Lagrangian multipliers associated with the time and multi-tasking constraints. Assuming interior solutions, optimizing with respect to the five choice variables results in the following first-order necessary conditions (FONCs). Defining $X_U \equiv HL + \phi NW$ and $X_P \equiv (\theta_1 S^{\rho} + \theta_2 (L + \beta W)^{\rho} + \theta_3 Z^{\rho} + \theta_4 K^{\rho})^{\frac{1}{\rho}}$, the FONCs are:

$$\frac{\partial \mathcal{L}}{\partial S} = M_1 \cdot M_2 \cdot M_3 \cdot \theta_1 \rho S^{\rho - 1} - \lambda_1 + \lambda_2 \alpha = 0 \tag{8}$$

$$\frac{\partial \mathcal{L}}{\partial L} = M_1 \cdot M_2 \cdot M_3 \cdot \theta_2 \rho (L + \beta W)^{\rho - 1} - \lambda_1 = 0 \tag{9}$$

$$\frac{\partial \mathcal{L}}{\partial W} = M_1 \cdot M_2 \cdot M_3 \cdot \theta_2 \rho (L + \beta W)^{\rho - 1} \beta - \lambda_2 = 0 \tag{10}$$

$$\frac{\partial \mathcal{L}}{\partial NW} = M_1 \cdot M_4 \cdot \phi - \lambda_2 = 0 \tag{11}$$

$$\frac{\partial \mathcal{L}}{\partial HL} = M_1 \cdot M_4 - \lambda_1 = 0, \tag{12}$$

[2] Given the structure of the two time-related constraints, the optimization problem only requires the choice of two out of three variables in $\{S, W, NW\}$. Appendix B recasts the problem with four choice variables, $\{S, L, NW, HL\}$, with section B.2 illustrating the equivalence between the two.

with the following introduced to ease notation:

$$M_1 \equiv \frac{\psi}{\eta}\left(\delta(PAX_P^{\gamma} - \tau R_Z Z + R_H H_{off} + V - B)^{\eta} + (1-\delta)X_U^{\eta}\right)^{\frac{\psi}{\eta}-1}$$
$$M_2 \equiv \delta\eta(PAX_P^{\gamma} - \tau R_Z Z + R_H H_{off} + V - B)^{\eta-1}$$
$$M_3 \equiv PA\left(\frac{\gamma}{\rho}\right)X_P^{\gamma-\rho}$$
$$M_4 \equiv (1-\delta)\eta X_U^{\eta-1}.$$

The above set of equations embed the market and non-market trade-offs experienced by households in optimally determining not only the time spent on work and non-work activities but also in how multi-tasked time is reinvested into work and/or non-work activities. One condition immediately apparent from equations (8)-(12) is the equality of the MRS between multi-tasked and dedicated work time, β, and the MRS between multi-tasked leisure time and dedicated leisure time, ϕ. This is because both multitasked work and multitasked leisure time share the same shadow value of multitasking time (λ_2), and both are scaled multiplicatively by single constants in otherwise identical CES nests.[3]

2.3 Comparative Statics

Of main interest are the effects of increased automation (α) on (1) the farmer's optimal division of time between farm work, off-farm work (H_{off}), and dedicated leisure (HL); (2) the time dedicated to automatable (S) and non-automatable tasks (L) within farm work tasks; and (3) the optimal allocation of work (W) and non-work (NW) time within time spent on automatable tasks.

Applying the Implicit Function Theorem to the set of FONCs yields expressions for $\frac{dS^*}{d\alpha}$, $\frac{dL^*}{d\alpha}$, $\frac{dNW^*}{d\alpha}$, and $\frac{dHL^*}{d\alpha}$, with $\{S^*, L^*, NW^*, HL^*\}$ representing optimal solutions for the four choice variables. Each of these expressions involve terms that represent normalized responsiveness of the FONCs to α. Some of these terms can be interpreted as scaled, weighted sums of marginal products and marginal utilities, reflecting how profitable or desirable additional effort becomes when α increases. See Appendix B for derivations of the partial derivatives needed to calculate these four comparative statics terms.

For further tractability and following related work in household production and time use models (Aguiar and Hurst, 2007; Aguiar et al., 2012; Aguiar and Hurst, 2013), we assume that farm household utility exhibits constant returns to scale (CRS), $\psi = 1$. Assuming that the above parameter ranges hold for $\{\delta, \eta, \rho, \beta, \phi, \tau, \theta_j\}$ for $j \in \{1, \ldots, 4\}$, then many of the individual terms in each of the four expressions can be signed. However, we are unable to definitively sign any of the comparative statics of interest due to the inherent complexity of the model. See Appendix section

[3]Generally, it is plausible, if not probable, that additional freed-up time in the cab could be more effectively redirected to work (or non-work) tasks, perhaps because of lack of reliable internet signal, operator attentional issues, or so on. A future extension of this work might introduce an estimable wedge parameter that could shed light on potential inequality in the marginal contributions of multi-tasked time.

B.1 for derivation of the expressions.

The intuition underlying these ambiguities differ based on each variable. For example, increasing automation improves the effectiveness of automated steering, but diminishing returns to S and substitution away from manual labor (L) could lead to a more complex reallocation of time rather than a simple expansion of S. The production function's diminishing returns ($\rho < 1$) limit the marginal benefit of additional auto-steering time. If steering time substitutes too strongly for other activities, S^* could even fall slightly. However, as automation increases, manual labor becomes less necessary. If steering time (S) and manual labor time (L) are at least partly substitutable, and if θ_2 is relatively low, then it is more likely that L^* would decrease as automation increases. Similar intuition holds for changes in NW: whether non-work time in the tractor cab increases depends on the gain in utility relative to productive work time in the cab (W) or dedicated leisure. Dedicated leisure, itself, could increase if automation brings about reductions in the need for manual labor and mental engagement. This form of leisure could be a natural outlet for reallocated time if C and HL are complements and the time inputs necessary for producing C exhibit diminishing returns. Ultimately, our model, while providing a useful framework for the problem, suggests the role of automation is mainly a question to be answered empirically and may vary by the empirical context and situation, which we turn to next.

3 Empirical Approach

Our multi-part empirical approach consists of four main stages: (1) deriving an estimating equation from the above set of FONCs, (2) approximating the technology parameter (α) and MRS between multi-tasked and dedicated work time (β), (3) using a control function approach to estimate parameters of the structural model, and (4) estimating the effects of technological improvement on the farmer's productivity, income, and time use. We discuss each of these in turn.

3.1 Deriving the Estimating Equation

One challenge in taking the model to the data is that little information exists on how farm operators allocate their multi-tasked time among W and NW. Some informal polls have been conducted in recent years, but these have tended to be information collection from small, non-random samples for purposes of news stories (e.g., Vogt, 2022). Arguably more important is that it has only been in recent years that auto-steer has become sufficiently quick and accurate to permit hands-off supervision. In the early 2000s, with the advent of automated steering and earlier versions (lightbars), the technology was more akin to assisted steering and tended to lose signal intermittently, suggesting that attention to leisure activities would have been limited (e.g., Griffin et al., 2005). Thus, while the technology helped to reduce operator fatigue, its leisure-based benefits in those years were negligible. To assist with estimation and ensure consistency with the nature of the technology during our sample period (2001-04), we will assume $NW \approx 0$.

By taking ratios of several equations in (8)-(12) and substituting out for X_P and X_U, we can

express total leisure time as a function of S, C, and X_P (see Appendix A):

$$HL + \beta NW = \left[\frac{\delta}{1-\delta}\frac{PA\gamma\theta_1}{1-\alpha\beta}\right]^{\frac{1}{\eta-1}} S^{\frac{\rho-1}{\eta-1}} \cdot C \cdot X_P^{\frac{\gamma-\rho}{\eta-1}}. \tag{13}$$

Taking logarithms of both sides, imposing $NW = 0$, substituting in $X_P = \left(\frac{Q}{A}\right)^{\frac{1}{\gamma}}$, and rearranging multiple terms results in:

$$\begin{aligned}\ln(HL) - \ln(C) = Cons + \left(\frac{1}{\eta-1}\right)\ln(\theta_1) + \left(\frac{1}{\eta-1}\right)\ln\left(\frac{\gamma}{1-\alpha\beta}\right) + \left(\frac{\rho}{\gamma(\eta-1)}\right)\ln(A) \\ + \left(\frac{1}{\eta-1}\right)\ln(P) + \left(\frac{\rho-1}{\eta-1}\right)\ln(S) + \left(\frac{\gamma-\rho}{\gamma(\eta-1)}\right)\ln(Q),\end{aligned} \tag{14}$$

where $Cons$ is a constant term. Substituting for Q and appending an econometric error term yields the following equation for field i in year t:

$$\begin{aligned}\ln(HL_{it}) - \ln(C_{it}) = Cons + \left(\frac{1}{\eta-1}\right)\ln(\theta_1) + \left(\frac{1}{\eta-1}\right)\ln\left(\frac{\gamma}{1-\alpha\beta}\right) + \left(\frac{\rho}{\gamma(\eta-1)}\right)\ln(A_{it}) \\ + \left(\frac{1}{\eta-1}\right)\ln(P_{it}) + \left(\frac{\rho-1}{\eta-1}\right)\ln(S_{it}) \\ + \left(\frac{\gamma-\rho}{\gamma(\eta-1)}\right)\left[\ln(A_{it}) + \frac{\gamma}{\rho}\ln\left(\theta_1 S_{it}^{\rho} + \theta_2(L_{it} + \beta\alpha S_{it})^{\rho} + \theta_3 Z_{it}^{\rho} + \theta_4 K_{it}^{\rho}\right)\right] + \epsilon_{it}.\end{aligned} \tag{15}$$

3.2 Approximating the Technology and Within-Cab Substitution Parameters

From (15), we see that the share, curvature, and homogeneity parameters $\{\eta, \rho, \gamma, \theta_j\}$ for $j \in \{1, \ldots, 4\}$ can be identified through standard estimation techniques.[4] However, α and β cannot be identified separately given that they appear only multiplicatively in the equation. In principle, we could introduce a shifter for α that changes only the multitasking window (αS) but not the efficiency of in-cab work (β), or conversely.[5] In the absence of additional exclusion restrictions or shifters associated with $\{\alpha, \beta\}$, we pre-estimate α using additional information from ARMS and calibrate β from UK time use dairy data and U.S. farm survey data, as outlined below.

Recall that $NW \approx 0$ implies that $\alpha \approx W/S$ or, alternatively, that $W = \alpha S$ from the multitasking time constraint. This suggests a regression-based approach can be taken to investigate the linkages between W and S. Specifically, we can regress time spent on the non-automatable tasks in the cab on total steering time, though with the recognition that multitasking time in the cab only comes about when automated guidance is adopted. Thus, for field i in year t, we could estimate:

[4] Note that δ is identified only up to a (multiplicative) constant, i.e., rescaling C and/or $H_{tot}^{leisure}$ (e.g., changing the monetary deflator or hours to days), would change the value of δ that would be recovered by naive estimation. Beyond this, the intercept term includes some of the other constants (scaled by $1/(\eta-1)$), and the set of fixed effects (FE) we include (explained in more detail below) soak up constant differences across groups that would otherwise be captured by $\ln(\delta/(1-\delta))$. While δ could be identified by fixing the relative scale of C and $H_{tot}^{leisure}$ or introducing a pure preference shifter that influences δ but not production, we follow the literature in remaining agnostic about the "true" value of this parameter (e.g., Aguiar and Hurst, 2007; Rogerson and Wallenius, 2013).

[5] Alternatively, we could introduce and estimate a reparameterization, $\kappa = \alpha\beta$, after pinning down α or β separately, which would allow us to back out the other parameter from $\hat{\kappa}$. We leave this as a robustness check for future work.

$$W_{it} = \mu S_{it} + \alpha \left(S_{it} \times G_{it} \right) + \varepsilon_{it}, \tag{16}$$

where $G_i \in \{0, 1\}$ is an indicator for autosteer adoption and ε_i is an econometric error term. If the operator does not use autosteer, $G_i = 0$, then all steering time is work time. However, based on our data, parts of W can occur outside the cab and thus not be tied to S (i.e., W can empirically co-move with S even if $G = 0$). Thus, our approximation of α is the incremental slope of W on S when guidance is present; that is, the extra in-cab work made possible by autosteer.[6]

For our dataset, we assume that time freed by autosteer can be allocated to three other tasks that can be performed (or checked on) in the equipment cab: scouting for weeds and insect pests, irrigation, and overhead activities (e.g., moving and loading materials, farm management). We make this assumption for data-related reasons: the field-level version of our main dataset, ARMS, only contains (non-machine) hours on these three tasks. Presumably, the farm operator could spend time on a wide variety of other freed-up tasks (e.g., coordinating equipment, monitoring diagnostics, routing hired workers, making field notes), few of which are tracked in ARMS or other representative field-level surveys. Although we would expect overhead activities to make up a large share of W, the three tasks we capture are still only a subset of feasible in-cab work activities, such that our α estimate should be interpreted as a lower-bound.[7]

We pool ARMS data on these task hours for years 2001-2004, add indicators for the scouting, irrigation, and overhead activities, a continuous measure of the commodity's enterprise acreage, and a set of fixed effects (FE), $\boldsymbol{X_i}$ (crop, year, state, and state-by-year). The resulting regression for field i in year t is:

$$W_{it} = \mu S_{it} + \alpha(S_{it} \times G_{it}) + \beta_S Scout_{it} + \beta_I Irrig_{it} + \beta_O Overhead_{it} + \beta_A Ac_{it} + \boldsymbol{\beta_X X_{it}} + \varepsilon_{it}. \tag{17}$$

Appendix C provides more details about the estimation approach, including a table of summary statistics for these data (Table C.1). Our regression results, shown in Table C.2, indicate $\hat{\alpha} \approx 0.30 - 0.31$, depending on model specification (with or without state-by-year FE). Importantly, as a validation check for this range of α, we developed a precision agriculture module for a well-known survey of Iowa farmers, the Iowa Farm and Rural Life Poll conducted at Iowa State University. Evidence from this survey suggests $\alpha \approx 0.35$, very close to our regression-based estimation.

Attempts at identifying β are more challenging since it is a largely unobserved efficiency parameter, similar to a weight that allows comparison of productivity of a multi-tasked work minute to a dedicated work minute. Ideally, β could be estimated from an experiment having a within-subjects

[6] By not including a level term for G_i, we assume that the only effect of autosteer on W comes via its interaction with S, i.e., that autosteer increases the amount of additional work that can be completed per unit of steering, not the level of work when $S = 0$. However, our estimate of α diminishes only slightly if we include the level effect.

[7] For example, suppose W^{true} is the true amount of in-cab work freed-up by autosteer, and W^{obs} is our constructed measure. Then we could represent $W^{obs} = p \times W^{true} + \nu$, where $p \in (0, 1]$ is the capture rate (fraction of in-cab work that our three categories cover out of the true total for W) and ν is a idiosyncratic noise. Then the regression we propose above identifies $p \times \alpha^{true}$ under the condition that p does not systematically vary with $S \times G$. In other words, measurement error in the dependent variable does not bias our OLS estimates; it scales the coefficient if the dependent variable is systematically undercounted.

design in which farmers are asked to complete a randomized (and externally-valid) set of muli-tasked work tasks (i.e., ΔW minutes of in-cab work with autosteer enabled) and dedicated-attention work tasks (i.e., ΔL minutes of the same task as done during dedicated work). A regression of any of various outcome measures (e.g., field pass overlaps or skips, crop moisture variance, or preferably yield monitor output) on L, W, and other controls would produce coefficient estimates such that $\hat{\beta}$ could be constructed from the ratio of the marginal products. However, in the absence of this kind of data, we instead use information about how individuals choose to allocate their multi-tasked time. Specifically, we rely on the most recent version (2014-15) of the UK Time Use Survey, a major time allocation survey in the English-speaking world that, unlike the American Time Use Survey, records information on respondents' simultaneous activities.

Our launching point for calibration of β is the idea that for individuals with fully automatable jobs, all of their work time is potential multi-task time. The degree to which they actually multi-task relative to the total opportunity to multi-task provides a rough approximation to β. This is in part because work performed in highly automatable jobs is cognitively similar to the kind of work done when autosteer is engaged. However, average time shares are not equal to the MRTS because they do not include any measures of marginal products. But in some simple model modifications, the time share can be shown to be monotonically related to β: when a worker decides how often to multitask (vs. focus) given an attention cost, the fraction of minutes used for multitasked work increases in β (holding the implicit opportunity set fixed).[8]

Appendix D describes in more detail our use of the 2014-15 UK Time Use Survey (UKTUS) and the multi-step process that we undertake to calibrate β. Broadly, we begin by matching occupational codes in the UKTUS and from Autor and Dorn (2013) to the UK Standard Occupational Classification (SOC) 2010 codes. We use Autor and Dorn (2013) since they provide a measure of routine task intensity (RTI), which allows us to determine which households' jobs are close to fully automatable.[9] For each individual in the UKTUS, we calculate total work time and multi-tasking time based on the responses they record in their diaries. We then construct average β estimates for each occupation code, and finally an overall estimate of β by averaging across all occupations with high automation potential based on the RTI scores.

This calibration procedure yields $\hat{\beta} \approx 0.32$, an approximation we use with caution in light of the issues noted above. However, studies in a variety of social sciences, including economics, have consistently found evidence that additional output from an extra unit of multitasked time is far

[8] For example, suppose that an operator must choose an amount of multi-tasked time $W \in [0, \alpha S]$ to optimize $B(W) = F(L + \beta W) - cW$, where $F(\cdot)$ describes output as a function of $(L + \beta W)$, with $F'(\cdot) > 0, F''(\cdot) < 0$, and $c > 0$ being the opportunity cost of attention. At an interior solution, $\beta F'(L + \beta W) = c$, or alternatively, $F'(L + \beta W) = \frac{c}{\beta}$. Because $F'(\cdot)$ is strictly decreasing, the right-hand side falling in β means that the left-hand side must also fall, suggesting that $L + \beta W$ must increase, and with it $W/(\alpha S)$.

[9] Autor and Dorn (2013) construct the RTI as $RTI_k = \ln\left(T_k^R\right) - \ln\left(T_k^M\right) - \ln\left(T_k^A\right)$, where T_k^R, T_k^M, T_k^A are measures of the routine, manual, and abstract nature of tasks performed in occupation k. Those measures derive from Autor et al. (2003), who assessed information from narratives and code in the fourth edition of the U.S. Department of Labor's *Dictionary of Occupational Titles*. As they note, the RTI measure is rising in the relative importance of routine tasks within an occupation and falling in the relative importance of manual tasks (the notion being that fully manual, non-routine tasks are harder to replicate by automation).

lower than from an extra unit of dedicated time. For example, Buser and Peter (2012) found that Dutch students randomly tasked with simultaneously completing certain kinds of puzzles (word searches and Sudoku) had substantially lower scores than those who completed these puzzles sequentially. In a related vein, Coviello et al. (2015) exploited (1) assignment of legal cases to judges by lottery in Italy, and (2) variation in the amount of case work done simultaneously versus sequentially. Controlling for caseload, the study found that judges who juggled cases in parallel took significantly longer to close the same total number of cases. Similar results have been shown in psychology experiments, such as Watson and Strayer (2010), who found that subjects assigned to a multi-tasking treatment (performing a complex memory-related activity with math problems) while engaged in a driving simulator took about 20% longer to brake in response to hazards and had substantially worse memory and math performance. Given this evidence, our estimate of $\hat{\beta} = 0.32$ is a conservative value that effectively implies a 70% loss in productivity due to multi-tasking, though we test robustness of this estimate using a range of plausible values.

3.3 Identifying Parameters of the Structural Model

Given values for α and β, and assuming Z and K are exogenously determined (e.g., by exogenous land requirements and decision-making occurring before in-season time allocations), the only other main challenge associated with estimating equation (15) is the endogenous nature of S and L. We address this using a two-stage control function framework in which we jointly estimate regression equations for both variables as a function of exogenous controls. Residuals from both equations (GR_S, GR_L) are then appended within the production function estimated in equation (15), serving as control functions (regressors $\xi_S GR_S$ and $\xi_L GR_L$) that mitigate potential bias from direct inclusion of S and L.

For identification of S, we rely on the engineering capacities of machinery used in field operations, as proxied by the minimum and maximum horsepower of the tractors used on the field. Available horsepower and the mix of horsepower largely determine implement width, field speed, the feasibility of pass plans, and uptime (McFadden, 2022; ASABE, 2020; White, 1977). These technologically shift how much in-cab steering time is required, independent of the farm household's tastes for leisure. We would expect these measures to be exogenous with respect to the second-stage error term because, while capital services enter the second stage directly through K, the horsepower variables represent pre-chosen capacity that affects S and not the relative utility of leisure versus consumption. In our specifications, we also include farm size controls (commodity enterprise quartiles), as well as fixed effects for crop, year, and county; these, taken together with our inclusion of pre-determined K and Z, help to limit any other direct path from horsepower to the disturbance term for $\ln(HL) - \ln(C)$ beyond the channel for S.[10]

[10] One potential worry is that higher horsepower is correlated with unobserved wealth, ability, or managerial quality, any of which could raise the household's taste for consumption or leisure (or otherwise shift the second-stage error term). However, since we are already accounting for K, horsepower would have to affect the preference shock for $\ln(HL) - \ln(C)$ directly and not through $\{S, L, Z, K\}$ or prices for a violation of the exclusion restriction, which seems less likely. Moreover, slow-moving wealth or ability are likely accounted for via county and year FE. Beyond

To identify L, we use a variety of local labor market conditions: state-level crop worker hourly wage rates and county-level per-capita personal incomes, shares of farm proprietor jobs, and unemployment rates. Collectively, these shift the opportunity cost and availability of manual farm labor (own labor and hired workers), altering how much dedicated manual time the operator supplies on-farm but not the technical capacity for in-cab steering. Our second-stage equation explains $\ln(HL) - \ln(C)$ through production inputs, prices, other farm-level controls, and an array of fixed effects; thus, these local labor-market conditions influence L and hired-labor availability but likely have no direct effect on the household's within-season MRS between HL and C after conditioning on prices, TFP, production inputs, and the fixed effects. Although it is possible that the county per-capita personal income measure could shift C directly, the fact that we control for local productivity and price variation, in addition to $\{S, L, Z, K\}$ and the various FE, absorb many channels through which local macro conditions could otherwise move.[11]

Given this identification strategy, our first-stage regression specifications for S and L on field i in year t take the form:

$$S_{it} = \beta_0^s + \beta_1^s \ln(HP_{it}^{Max}) + \beta_2^s \ln(HP_{it}^{Min}) + \boldsymbol{\beta_D^s D_{it}} + \boldsymbol{\beta_F^s F_{it}} + \boldsymbol{\beta_X^s X_{it}} + \varepsilon_{it}^s \tag{18}$$

$$L_{it} = \beta_0^l + \beta_1^l WR_{it} + \beta_2^l PCPI_{it} + \beta_3^l SH_{it} + \beta_4^l UR_{it} + \boldsymbol{\beta_D^s D_{it}} + \boldsymbol{\beta_F^s F_{it}} + \boldsymbol{\beta_X^s X_{it}} + \varepsilon_{it}^l, \tag{19}$$

where $\ln(HP_{it}^{Max})$ and $\ln(HP_{it}^{Min})$ are logarithms of the maximum and minimum horsepower of the tractors used on the field and $\{WR_{it}, PCPI_{it}, SH_{it}, UR_{it}\}$ are the four local labor market variables discussed above (state cropworker wage rate, county per-capita personal income, county share of farm proprietor jobs, and county unemployment rate, respectively). To control for operator-related socioeconomic characteristics that could influence the efficiency of work time, we include several demographic variables in the vector $\boldsymbol{D_{it}}$, including whether the farm operator is hired, whether contract labor is hired for the field, and the operator's (log) age, race (an indicator being white), and education (an indicator for having any college education). The vector $\boldsymbol{F_{it}}$ contains field- and farm-related attributes that we deem likely to have direct bearing on steering and manual labor time: an indicator for whether the field is producing grains, oilseeds, cotton, or hay in the current season; an indicator for whether the field has been classified by USDA as being highly erodible; per-acre custom labor costs and per-acre seed, fertilizer, and chemical application costs; and an indicator for whether the field required a number of equipment passes greater than the sample median. The vector $\boldsymbol{X_{it}}$ includes farm size quartiles, crop FE, year FE, and geographic FE at various spatial scales (state, crop reporting district, and county).[12]

Because common idiosyncratic shocks could affect both steering and manual work time contemporaneously (e.g., day-to-day task coordination noise, common respondent noise), we estimate

this, any residual correlation between S and the second-stage error is soaked up by the generalized residual.

[11] We also note that our results in both stages are qualitatively robust to dropping the per-capita personal income instrument.

[12] USDA's National Agricultural Statistics Service (NASS) defines crop reporting districts (CRDs) as collections of counties with similar crop production characteristics based on a number of factors. Many states, though not all, have nine CRDs (USDA-NASS, 2025b).

equations (18)-(19) using seemingly unrelated regression (SUR). This produces more efficient estimates and lower-variance generalized residuals, improving the quality of the endogeneity correction in the second stage. With generalized residuals $(\hat{GR}_S, \hat{GR}_L)$, we estimate the second stage as:

$$\begin{aligned}\ln(HL_{it}) - \ln(C_{it}) = Cons &+ \left(\frac{1}{\eta-1}\right)\ln(\theta_1) + \left(\frac{1}{\eta-1}\right)\ln\left(\frac{\gamma}{1-\alpha\beta}\right) + \left(\frac{\rho}{\gamma(\eta-1)}\right)\ln(A_{it}) \\ &+ \left(\frac{1}{\eta-1}\right)\ln(P_{it}) + \left(\frac{\rho-1}{\eta-1}\right)\ln(S_{it}) + \left(\frac{\gamma-\rho}{\gamma(\eta-1)}\right)\cdot \\ &+ \left[\ln(A_{it}) + \frac{\gamma}{\rho}\ln\left(\theta_1 S_{it}^{\rho} + \theta_2(L_{it}+\beta\alpha S_{it})^{\rho} + \theta_3 Z_{it}^{\rho} + \theta_4 K_{it}^{\rho} + \xi_S \hat{GR}_S + \xi_L \hat{GR}_L\right)\right] \\ &+ \boldsymbol{\beta_X X_{it}} + \epsilon_{it},\end{aligned} \tag{20}$$

where $\boldsymbol{X_{it}}$ contains farm size quartiles, crop FE, year FE, geographic area (farm resource region, state, or CRD) FE and geographic area-by-year FE.[13]

3.4 Estimating the Effects of Increased Automation (Elasticities)

Estimation of the effects of increased automation relies on calculation of the various terms involved in the closed-form expressions for $\frac{dS^*}{d\alpha}$, $\frac{dL^*}{d\alpha}$, $\frac{dNW^*}{d\alpha}$, and $\frac{dHL^*}{d\alpha}$ (available in Appendix B). In particular, we calculate equations (B.14)-(B.17), with the partial derivatives needed for these defined later in the appendix. Because α is a unitless parameter, we ease interpretation by instead calculating elasticities, i.e., the percent change in these variables when α increases by one percent.[14] However, since $\alpha \in (0,1)$ does not map to specific technologies, nor do increases in α represent the progress of specific technologies, the main point of the elasticity estimates is to provide empirical evidence about their signs and sketch out magnitudes.

We can derive an expression for the elasticity of W^* with respect to α by differentiating the multi-tasking constraint, equation (6):

$$\frac{dW^*}{d\alpha} + \frac{dNW^*}{d\alpha} = \frac{d}{d\alpha}\left(\alpha S^*\right),$$

which implies that $\frac{dW^*}{d\alpha} = S^* + \alpha \cdot \frac{dS^*}{d\alpha} - \frac{dNW^*}{d\alpha}$. Thus, we can recover $\left(\frac{dW^*}{d\alpha}\frac{\alpha}{dW^*}\right) \equiv \epsilon_{W^*\alpha}$ after calculating the responsiveness of S^* and NW^* to changes in α.

One challenge in calculating the elasticities is that we assume $NW = 0$ in estimating equation (20). This implies the point elasticity, $\left(\frac{dNW^*}{d\alpha}\frac{\alpha}{NW^*}\right) \equiv \epsilon_{NW^*\alpha}$, is undefined. To circumvent this issue, we assume that NW represents a small share of the time available for multitasking such that $NW = 0.05S$; this assumption is only made for purposes of calculating this elasticity and in no other components of the analysis. That is, we assume $NW^* = \sigma_{NW}\alpha S^*$ and $W^* = (1-\sigma_{NW})\alpha S^*$. We set $\sigma_{NW} \approx 1/6$, i.e., non-work time takes up roughly 16.7% of the time available for multi-tasking.

[13] ERS farm resource regions are clusterings of counties that group areas with similarities based on farm characteristics, land resources, and production characteristics. With only nine regions, these are more highly aggregated than a state-level delineation (Heimlich, 2000).

[14] Given that $\hat{\alpha} = 0.30$, a one percent change represents $\Delta\hat{\alpha} = 0.003$, suggesting we should expect small elasticities.

For plausible values of this share, say $NW^* \in [0, 0.15S^*]$, we can see that $\epsilon_{W^*\alpha}$ is reasonable and expected to be slightly above one.[15]

Two other clarifications remain. First, to introduce more realism to the model, we assume that local increases in α do not affect H_{off}, i.e., any potential extensive margin effect of small increases in automation on off-farm work is assumed to be zero. This is consistent with the notion that early autosteer technologies in our sample period continued to require consistent focus for operation (e.g., Schimmelpfennig and Ebel, 2016). Therefore, we set $H_{off} = 0$ in the elasticity calculations for farm households that did not supply any off-farm work in the baseline. However, when S or L is increased by a minute at the corner, the operator is no longer giving up a minute of H_{off} worth R_h. Underlying equations (B.14)-(B.17) are several wage-scaled penalty terms involving R_h that are removed (their inclusion otherwise would overstate the marginal time cost). Second, to avoid the influence of extreme values for a small set of observations, we present the interdecile range of the calculated elasticities. This is relatively more important for $\epsilon_{S^*\alpha}$ and $\epsilon_{L^*\alpha}$, which can be large for some operations due to small S and/or L, as well as due to certain wage-weighted terms that cause the ratio to be large.

4 Data

Our analysis combines several micro-level and aggregate datasets of farm, household, and regional variables. The core data come from the USDA's Agricultural Resource Management Survey (ARMS), specifically the Phase II and Phase III surveys for years 2001–2004 (USDA-ERS, 2025b). The Phase II data provide detailed field-level information on production practices and inputs for a target commodity (one field per farm in the survey year), while Phase III provides farm-level financial and labor information for the same operations. We focus on seven major field crops—barley, corn, cotton, peanuts, sorghum, soybeans, and wheat—surveyed over 2001–2004, yielding a combined sample of crop-specific enterprise-seasons.[16] Each observation in our dataset corresponds to a farm growing one of these crops in a given year, with the field-level and farm-level ARMS data merged by operation.[17]

We augment the ARMS microdata with several external sources to incorporate prices and regional economic conditions. State-average commodity output prices (P) for each crop-year come from the National Agricultural Statistics Service (NASS) Agricultural Prices data (USDA-NASS, 2025b). State-level agricultural total factor productivity (A) indexes are drawn from USDA-ERS

[15] This is because $\epsilon_{W^*\alpha} = \frac{1}{1-\sigma_{NW}} + \frac{\alpha^2}{W^*}\frac{dS^*}{d\alpha} - \frac{\alpha}{W^*}\frac{dNW^*}{d\alpha}$, using the fact that $W^* = (1-\sigma_{NW})\alpha S^*$ implies $\frac{\alpha S}{W} = \frac{1}{1-\sigma_{NW}}$. Thus, if $\frac{dS^*}{d\alpha}$ and $\frac{dNW^*}{d\alpha}$ are small, then $\epsilon_{W^*\alpha} \approx \frac{1}{1-\sigma_{NW}}$.

[16] The ARMS sample design targets geographic representativeness such that our pooled data cover farms across the country's major production regions for these crops.

[17] To ensure that key structural variables are in enterprise-season units, we rescale field- and farm- data based on the ratio of crop enterprise acres to total farm acres. In many instances, we redefine variables to be in per-acre units and then multiply by enterprise acreage. We use the ratio of season months to total months to rescale data reported on annual level, where the season is defined as the number of months elapsed between the first and last field operation.

productivity accounts (USDA-ERS, 2025a). Local labor market conditions are captured by a state-level mean hourly wage rate for farm equipment operators (WR) (BLS, 2025b) and by county-level unemployment rates (UR) (BLS, 2025a). Similarly, we control for regional economic characteristics by using county-level per capita personal income ($PCPI$) and the farm proprietor employment share (SH) from the BEA CAINC30 regional income tables (BEA, 2025). We also use NASS Prices Paid Index data on farm inputs (seeds, fuel, fertilizers, and chemicals) to deflate expenditures and construct the variable input quantity (Z) index (USDA-NASS, 2025b). Appendix E contains more information about the construction of key variables used for the analysis.[18]

We also include various controls and FE grouping variables. We use the farm operator's demographics from ARMS Phase II (age, education, race) and farm characteristics such as total farm size and indicators for farm type (based on commodity types with the largest share of gross farm income). We also capture machinery and production environment variables from ARMS Phase II: the maximum and minimum tractor horsepower used on the field, whether the field had above-median passes, whether any contract labor was used on the field, and whether the principal operator was a hired manager rather than an owner-operator. These additional variables help control for heterogeneity in production practices and farm organization. Beyond these, we include various FEs to absorb location- and commodity-specific unobservables, including crop type, year, area, and area-by-year. Areas can be defined broadly or narrowly, and we test both ERS Farm Resource Regions and NASS Crop Reporting Districts, as well as state-by-year FEs in some specifications.[19]

Table 2 presents summary statistics for the major variables in our dataset. On average, a farm operator devoted about 100 hours per season to steering machinery in the target enterprise during 2001-04, compared to roughly 430 hours of other farm labor (L) in that enterprise. Slightly more variation exists in manual labor hours than steering hours, reflecting underlying heterogeneity in the kinds of tasks that are performed on farms of various sizes. By contrast, total season leisure hours are 1,257; this is just over eight hours per day if the crop season lasts five months, which is reasonable since these hours include sleep time, by construction.[20]

The average crop enterprise in our data produced 1.1 million pounds of output in the season, the expected order of magnitude given average enterprise sizes, yields, and the fact that nearly 75% of our sample were growing corn or soybeans. Coupled with an average output price of about \$0.07/lb, this implies annual gross revenue on the order of \$75,000 per farm for the commodity enterprise, consistent with average gross cash farm income of \$79,000-\$99,000 per farm reported in these years (USDA-ERS, 2025c). Average per-acre expenditures on seeds, fuel, fertilizers, and

[18] We apply two cleaning steps to ensure sensible variables definitions. First, continuous variables that exhibit skewness (e.g., input expenditures, output, farm size) are winsorized at the 1st and 99th percentiles by crop and year to mitigate the influence of outliers. Second, variables that are conceptually non-negative, such as hours and expenditures, are forced to be non-negative (e.g., if the calculation of HL yielded a slight negative due to over-reported work hours, we set HL to zero).

[19] These FEs help to soak up any baseline differences in outcomes across states or regions that could be correlated with autosteer adoption. By accounting for this spatial and temporal heterogeneity, identification comes from within-region, within-period variation (e.g., adopters vs. non-adopters in the same area and year).

[20] A five month window is a reasonable approximation to the average season duration since our season measure typically includes pre-plant and post-harvest operations.

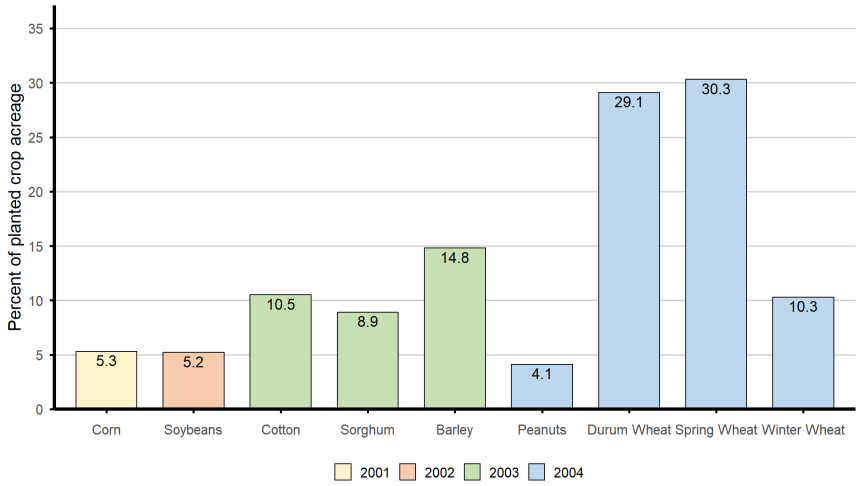
Table 2: Summary Statistics for Key Variables

Variable	Unit	Area	Mean	Std. Error	95% CI Lower	95% CI Upper
Steering time (S)	Operator's hours	Operator-season	100	3.5	92	107
Labor time (L)	Operator's hours	Operator-season	430	11.2	406	454
Variable input (Z)	Index	Enterprise-season	129	4.6	119	139
Capital assets (K)	Nominal USD	Enterprise-season	320,008	10,312	297,891	342,125
Crop output (Q)	Pounds	Enterprise-season	1,112,436	29,262	1,049,676	1,175,196
Total leisure time (HL)	Operator's hours	Operator-season	1,257	30.8	1,191	1,323
Consumption (C)	Nominal USD	Household-season	6,234	239.2	5,721	6,747
Auto-steer use (G)	{0,1}	Field	0.040	0.006	0.027	0.054
Total factor productivity (A)	Index	State	1.13	0.006	1.12	1.14
Output price (P)	$/lb	State	0.068	0.001	0.066	0.071
Maximum horsepower (HP^{Max})	Tractor HP	Field	164	2.1	159.4	168.4
Minimum horsepower (HP^{Min})	Tractor HP	Field	112	0.9	110.1	114.1
Above median no. of passes	{0,1}	Field	0.406	0.014	0.376	0.436
Principal operator is hired	{0,1}	Farm	0.011	0.003	0.004	0.018
Contract labor used	{0,1}	Field	0.016	0.005	0.006	0.026
Operator's age	Years	Farm	52.9	0.35	52.1	53.6
Any college	{0,1}	Farm	0.440	0.013	0.413	0.468
White operator	{0,1}	Farm	0.958	0.005	0.948	0.968
Grain-oilseeds-cotton-hay farm	{0,1}	Farm	0.745	0.013	0.718	0.772
Erodible land	{0,1}	Field	0.216	0.011	0.192	0.240
Total farm size	Acres	Farm	792	23.1	742	841
Custom service costs	$/ac	Enterprise	0.184	0.051	0.074	0.294
Seed, fuel, fert, & chem expenditures	$/ac	Enterprise	101	11.0	78	125
Crop worker wage rate (WR)	$/hour	State	8.36	0.02	8.31	8.41
Per capita personal income ($PCPI$)	Nominal USD	County	26,177	120.8	25,918	26,436
Share farm proprietor jobs (SH)	Fraction	County	0.083	0.002	0.079	0.086
Unemployment rate UR	Fraction	County	0.048	0.001	0.047	0.049
Barley	{0,1}	Field	0.026	0.003	0.021	0.031
Corn	{0,1}	Field	0.412	0.012	0.387	0.438
Cotton	{0,1}	Field	0.018	0.002	0.014	0.021
Peanuts	{0,1}	Field	0.007	0.001	0.005	0.010
Sorghum	{0,1}	Field	0.036	0.006	0.023	0.049
Soybeans	{0,1}	Field	0.337	0.011	0.313	0.361
Wheat	{0,1}	Field	0.164	0.013	0.136	0.192
Year 2001	{0,1}	—	0.412	0.012	0.387	0.438
Year 2002	{0,1}	—	0.337	0.011	0.313	0.361
Year 2003	{0,1}	—	0.080	0.007	0.065	0.094
Year 2004	{0,1}	—	0.171	0.013	0.143	0.199

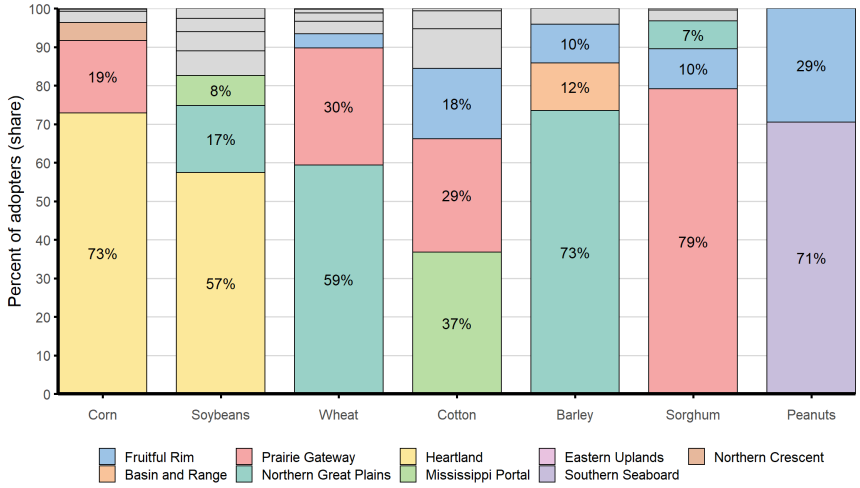
Notes: Abbreviations: 95%CI Upper and 95%CI Lower indicate the upper and lower ranges of the 95% confidence interval. Sample size (n) = 4,742. Standard errors have been jackknifed using the delete-a-group jackknife method with NASS-provided replicate weights. Unless otherwise noted, all variables have been scaled to the commodity enterprise level for the growing season using information about enterprise acreage, farm acreage, and season duration. The input vector (Z) is the sum of crop enterprise expenditures on seeds, fuel, fertilizer, and chemicals, each of which is adjusted by NASS' Prices Paid Index for each input type (USDA-NASS, 2025a). Table E.1 contains notes and more information about the data sources for each variable.

chemicals were $101, which aligns with per-acre estimates of these costs in 2001-04 of $119-$147 for corn, $57-$64 for soybeans, and $40-$52 for wheat (USDA-ERS, 2025d). The average value of the capital stock was $320,000, with the 95% confidence interval ranging in $298,000-$342,000.

Importantly, only 4% of sample fields used autosteer, reflecting the early adoption stage of this technology in the early 2000s. This low overall adoption rate belies differences across farm types: larger corn and soybean operations in the Midwest, as well as wheat farms, were the primary adopters, while fewer peanut farms in the sample used autosteer (Figure 1(a) and 1(b)). Autosteer adoption rates are also highly correlated with farmer demographics (e.g., Schimmelpfennig, 2016; McFadden et al., 2022). Over the sample period, the average operator was 53 years old, and 44% of them had received at least some undergraduate university credit.



(a) National Adoption by Crop and Year



(b) Top 3 Regions of Adopters by Crop and Year

Figure 1: Autosteer Adoption in the United States, Years 2001-04

5 Results and Discussion

We overview the results from the first stage regressions and parameter estimates from the second stage regressions below, as well as the implied elasticities with respect to increases in automation. To shed more light on the implications of our estimates, we simulate the effects of changes to our benchmark parameters on farm net returns, off-farm income, and total household income. We then decompose these effects by mechanism: (1) steering time, (2) manual labor time, (3) variable input expenses, and (4) off-farm work time.

5.1 First-Stage Results

Table 3 presents the first-stage regression results. We find the excluded instruments have generally high relevance for their respective endogenous variables. In particular, the maximum and minimum tractor horsepower are strong predictors of steering hours, with ln(Max HP) positive and significant at the 1% level and ln(Min HP) negative and significant. As expected, this suggests that farms with larger, more powerful equipment devote more time to steering, even after controlling for farm size (acreage quartiles). Likewise, local labor market conditions shift the supply of manual labor. A higher crop-worker wage rate reduces operator labor hours, consistent with costly hired labor inducing farmers to supply less on-farm labor themselves. Although this finding is counterintuitive under the assumption that operators and (hired) cropworkers are substitutes, the fact that few operations relied on hired labor in our sample and tight agricultural labor markets in the Midwest suggest that this wage rate is most likely reflecting operators' farm-work opportunity costs. Similar interpretations exist for the negative effects of per capita personal income (significant at the 1% level when using county FE) and the county share of farm proprietor jobs.

Table 3: First-Stage Seemingly Unrelated Regression (SUR) Results

	Steering Hours			**Labor Hours**		
	(1a)	(2a)	(3a)	(1b)	(2b)	(3b)
ln(Max HP)	0.181***	0.168***	0.204***	—	—	—
ln(Min HP)	−0.064*	−0.072*	−0.120***	—	—	—
Crop worker wage rate	—	—	—	−0.190***	−0.142***	−0.079
Per capita personal income	—	—	—	−0.000	−0.000	−0.000***
Share farm proprietor jobs	—	—	—	−0.008***	−0.007***	−0.147***
Unemployment rate	—	—	—	−0.015	−0.018	−0.049
Principle operator is hired	−0.033	0.008	0.002	0.004	0.009	0.086
Contract labor used	0.062	0.060	−0.037	0.143*	0.100	0.076
ln(Operator's age)	−0.005	−0.020	−0.001	−0.291***	−0.314***	−0.359***
Any college	−0.039	−0.042	−0.040	−0.005	−0.018	−0.026
White operator	0.112*	0.099	0.065	−0.025	−0.019	0.002
Custom service costs/ac	−0.103***	−0.102***	−0.124***	−0.052***	−0.050***	−0.048***
ln(Variable input costs/ac)	−0.155***	−0.155***	−0.157***	−0.032*	−0.032*	−0.037*
Above median no. of passes	0.381***	0.390***	0.366***	0.213***	0.216***	0.182***
Erodible land	0.015	−0.004	0.025	−0.016	−0.011	−0.022
Grain-oilseeds-cotton-hay farm	0.255***	0.276***	0.249***	0.081**	0.067**	0.043
Quartile 2, total farm size	0.599***	0.601***	0.610***	0.130***	0.132***	0.111**
Quartile 3, total farm size	0.984***	0.979***	1.020***	0.250***	0.236***	0.226***
Quartile 4, total farm size	1.453***	1.464***	1.497***	0.331***	0.312***	0.275***
Constant	−1.588***	−1.740***	−1.032**	3.050***	4.061***	4.038***
R^2	0.38	0.42	0.59	0.19	0.26	0.49
Year FE	No	No	No	No	No	No
Crop FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	No	No	Yes	No	No
CRD FE	No	Yes	No	No	Yes	No
County FE	No	No	Yes	No	No	Yes
Observations	4,892	4,892	4,892	4,892	4,892	4,892

Notes: Max HP = maximum horsepower, Min HP = minimum horsepower, CRD = NASS crop reporting district. To aid convergence, steering hours have been log-scaled and labor hours have been standardized (but are not mean zero). Robust standard errors (clustered at the county level) are omitted for space considerations. Year FE were omitted due to substantial collinearity with the crop FE. Significance is denoted as $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Chi-squared statistics (not shown) exceed critical values at the 1% level.

Several of the operator, enterprise, and farm controls are also significant predictors of on-farm work time. Among these, farm size is a major driver, with large and increasing effects in

both the steering hours and labor hours equations, and similarly for the indicator of whether the operator of the surveyed field had an above-median number of field passes.[21] Higher custom service costs per acre are associated with lower operator steering and labor hours, in part because after controlling for acreage and the number of passes, these costs mainly reflect the share of custom operations performed.[22] Moreover, older operators supply significantly fewer labor hours than younger operators, though age does not have a clear effect on steering hours; this is in line with expectations that steering is less physically demanding than many of the tasks captured in L.

5.2 Structural Model Estimation Results

Table 4 reports the estimated values of the model's reparameterized structural coefficients (denoted e_1, t_2, t_3, t_4, g_1 and d_1) obtained from the second-stage nonlinear regression under various fixed-effect specifications. These coefficients correspond to the underlying structural parameters of interest (see Appendix A). The estimate of e_1 is positive and significant across all specifications, ranging roughly from 0.95 to 1.80 (with significance at the 5% level or better in most cases). The estimate for g_1 is small and positive in all specifications and generally significant at the 10% level. However, the three t-parameters (t_2, t_3, t_4) are estimated with large standard errors and are not significant in any specification. The estimates for d_1 are small and negative, consistent with the requirement that the production substitution parameter (ρ) be less than one, and are generally only statistically significant in the more saturated models (columns 7 and 8).

The generalized residuals for steering and labor are small and generally insignificant, with the exception of GR_L in the saturated models. Figure 2 shows the control function approach yields generally well-behaved, mean-zero residuals, ruling out any serious issues associated with scale or outliers. The lack of significance of the $t-$statistics, which are essentially variable additions tests, suggests that endogeneity bias for S and L is not severe (e.g., Wooldridge, 2014, 2015).

Table 5 contains the structural parameter estimates of interest. In our preferred specification with more robust fixed effects (models 7 - 8), the steering input (S) accounts for roughly one-third of effective farm output ($\theta_1 \approx 0.33$), underscoring the importance of steering time in production. The operator's manual labor (L) has a much smaller share ($\theta_2 \approx 0.05$), indicating that the principal operator's direct labor contributes relatively little to output at the margin. Instead, the bulk of output is attributed to variable inputs ($\theta_3 \approx 0.23$) and capital ($\theta_4 \approx 0.39$), which includes land and equipment. These estimates align with intuition and data: farm production is heavily driven by

[21] The number of field passes could be considered to be endogenous to the quantity of steering hours because passes are partly a choice variable. If the number of passes are correlated with any unobserved productivity in the second stage, bias could result. However, this does not threaten identification of θ_1 or θ_2 in the second stage. We keep the passes variable in the first stage as it helps to proxy for operation intensity, though we note the results are robust to dropping the variable.

[22] For example, let p_n be the number of passes per acre for field operation n, c_n be the custom price per acre per pass, and s_n be the share of operation n that is done by custom service providers. Then custom costs per acre are $\sum_n s_n \cdot p_n \cdot c_n$ and the operator's own hours per acre are approximately $\sum_n (1 - s_n) \cdot p_n \cdot h_n$, where h_n is the operator's own hours per acre per pass for operation n. By including the above-median number of passes, we are coarsely controlling for p_n, and the fixed effects are soaking up much of the variation in c_n. The remaining cross-sectional variation in the variable is then mainly due to s_n.

Table 4: Second Stage Nonlinear Regression, Parameter Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
e1	1.770**	1.799***	1.147*	1.189*	1.480***	0.952*	1.081*	1.115*
	(0.669)	(0.661)	(0.612)	(0.633)	(0.323)	(0.548)	(0.559)	(0.619)
t2	−0.766	−0.551	−0.707	−0.714	−0.387	−0.844	−2.087	−1.915
	(1.726)	(1.638)	(1.677)	(1.697)	(2.030)	(1.679)	(4.013)	(3.664)
t3	−0.177	−0.471	−0.754	−1.017	−0.924	−1.106	−0.349	−0.359
	(1.628)	(1.717)	(1.866)	(1.986)	(2.320)	(1.910)	(1.992)	(1.970)
t4	−0.867	−0.481	−0.639	−0.259	0.008	−0.353	0.111	0.171
	(1.812)	(1.749)	(1.872)	(1.686)	(1.931)	(1.620)	(1.491)	(1.465)
g1	0.469**	0.479*	0.240	0.228	0.264**	0.171*	0.139	0.151
	(0.293)	(0.286)	(0.152)	(0.148)	(0.119)	(0.104)	(0.085)	(0.101)
d1	−1.076	−1.060	−1.338	−1.394	−1.189	−1.522	−1.668**	−1.631**
	(1.006)	(0.900)	(1.062)	(0.982)	(0.942)	(0.929)	(0.823)	(0.815)
Gen. Resid. (GR_S)	−0.037	−0.021	0.011	0.017	0.019	0.015	0.013	0.014
	(0.058)	(0.056)	(0.027)	(0.017)	(0.023)	(0.014)	(0.012)	(0.012)
Gen. Resid. (GR_L)	−0.036	−0.063	−0.081	−0.080	−0.064	−0.071	−0.0761*	−0.0761*
	(0.099)	(0.095)	(0.063)	(0.068)	(0.109)	(0.061)	(0.040)	(0.041)
Crop FE	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	No	No	No	Yes	Yes
Region FE	No	Yes	No	No	Yes	Yes	No	No
State FE	No	No	Yes	Yes	No	No	No	No
State × Year FE	No	No	No	No	Yes	Yes	No	No
CRD FE	No	No	No	No	No	No	Yes	Yes
Region × Year FE	No	No	No	Yes	No	No	No	Yes
Farm Size Quartiles FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N (obs)	4,386	4,386	4,386	4,386	4,386	4,386	4,386	4,386

Notes: Gen. Resid. = generalized residuals, FE = fixed effects. Appendix A provides more information about the relationships between $(e_1, t_2, t_3, t_4, g_1, d_1)$ and the structural parameters of interest. Coefficients are estimated from nonlinear regressions using NASS-provided survey weights. Significance is denoted as $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

capital and variable inputs, with the operator's time playing a smaller role. However, we are not able to reject the hypothesis that the shares are equal ($p = 0.99$). This is in large part due to the fact that in estimation, S^ρ and $(L + \alpha\beta S)^\rho$, are highly correlated, with perhaps a flat likelihood over (t_1, t_2). Because the input shares sum to one, uncertainty in θ_1 and θ_2 spill over to θ_3 and θ_4, which is exacerbated by correlation between Z and K.[23]

The estimated production function curvature (γ) is 1.1-1.2 and not statistically different from one, indicating constant returns to scale in production, in line with many past findings for US crop production. The input substitution parameter (ρ) is around 0.70-0.80, corresponding to an elasticity of substitution of 3-5, which suggests a relatively high degree of substitutability among inputs. Within the structure of our underlying model, this elasticity is intuitive: automated steering can replace manual labor to some extent, as can capital. However, our η value of -2 corresponds to an elasticity of substitution between consumption and leisure of roughly 0.3, indicating a high degree of complementarity. Intuitively, the household does not value "free time" in isolation highly unless it is accompanied by adequate spending or other leisure-enhancing goods. This result is consistent with prior literature finding limited willingness to trade off leisure for income at the margin in households, i.e., that additional income does not result in large changes in hours worked (and thus leisure) (e.g., Huffman, 1980; Chetty et al., 2011), and it will influence how any freed-up time from automation is utilized.

[23]The estimation procedure can trade off changes in the θ_j parameters with ρ and γ to fit the data, which can flatten the likelihood in directions related to (θ_3, θ_4) and inflate their standard errors.

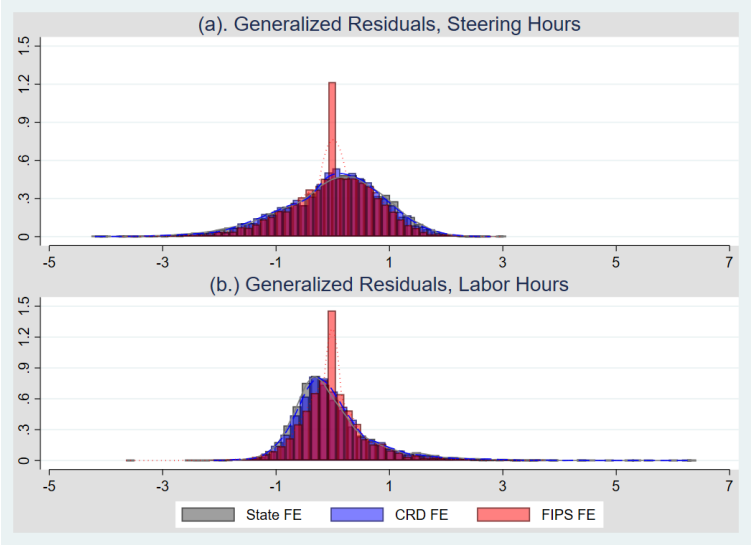


Figure 2: Histograms of the Generalized Residuals from First Stage Seemingly Unrelated Regression (SUR) Results for Steering and Labor Hours

5.3 Farm Household Elasticities of Time, Labor, and Leisure

Figure 3 shows histograms of the elasticities of the main model parameters with respect to the technology parameter, specifically measuring changes in S, L, W, NW, and HL that result from a one percent change in α. Several clear patterns emerge. First, autosteer increases have the largest proportional effects on multitasked work (W), with an elasticity in 1.20-1.28. The magnitude is intuitive and closely related to our assumption that roughly $(\frac{5}{6})$th of the multitasking window is used productively. This result aligns with our model's implication that the shadow value of the multitasking time split between work and leisure is equal. We further find near-zero elasticities for in-cab leisure and dedicated leisure, suggesting that operators reallocate potential idle time to production. This is consistent with our finding of strong complementarity between consumption and leisure ($\eta \approx 2$). Although the distribution of $\epsilon_{HL^*\alpha}$ is bunched at zero, the slight right tail indicates a small number of farmers might enjoy a very small increase in dedicated leisure.

We estimate a negative elasticity of manual labor hours with respect to automation for nearly all farmers, averaging in the range of [-0.09,-0.01]. This indicates a modest substitution of autosteer for the operator's other farm work: as the technology improves, the farmer can slightly cut back on hands-on labor. In some cases, the reduction in L is larger (the distribution's left tail approaches –0.1 or lower), likely for farms where previously the operator spent many hours on manual tasks that can now be partially done in the cab. However, the change in manual labor is small, consistent with diminishing returns and the low baseline labor share. Labor declines because automation makes manual effort "less necessary," and the operator reallocates effort toward the more efficient input (steering) with a limited "output penalty" (since θ_2 is so low). Note that the decline in L is not one-for-one with the increase in W; part of the new multitasking work substitutes for what the operator would have done inside the cab, which is an expected effect of autosteer adoption.

Table 5: Second Stage Nonlinear Regression, Structural Model Parameters

Parameter	Notation	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Steering (S) share	θ_1	0.367	0.355	0.401	0.381	0.324	0.406	0.339	0.330
Labor (L) share	θ_2	0.171	0.204	0.198	0.187	0.220	0.174	0.042	0.049
Variable input (Z) share	θ_3	0.308	0.221	0.189	0.138	0.129	0.134	0.239	0.230
Fixed capital (K) share	θ_4	0.154	0.219	0.212	0.294	0.327	0.285	0.379	0.391
Production substitution parameter	ρ	0.659	0.653	0.738	0.752	0.696	0.782	0.811	0.804
Utility substitution parameter	η	−4.874	−5.046	−2.149	−2.283	−3.392	−1.592	−1.949	−2.050
Degree of homogeneity	γ	1.599	1.615	1.271	1.256	1.302	1.187	1.149	1.163
Elasticities of substitution									
Between inputs (S, L, Z, K)	$\frac{1}{1-\rho}$	2.93	2.88	3.82	4.03	3.29	4.59	5.29	5.10
Between utility factors (C, H_{tot}^{leis})	$\frac{-1}{\eta-1}$	0.17	0.17	0.47	0.44	0.29	0.39	0.34	0.33
Crop FE	—	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
Year FE	—	Yes	Yes	Yes	No	No	No	Yes	Yes
Region FE	—	No	Yes	No	No	Yes	Yes	No	No
State FE	—	No	No	Yes	Yes	No	No	No	No
State × Year FE	—	No	No	No	No	Yes	Yes	No	No
CRD FE	—	No	No	No	No	No	No	Yes	Yes
Region × Year FE	—	No	No	No	Yes	No	No	No	Yes
Farm Size Quartile FE	—	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Fixed effects (FE) shown as included (Yes) or excluded (No) by model specification. Elasticity of substitution across inputs is $\sigma = \frac{1}{1-\rho}$. Elasticity of substitution between consumption and total leisure is $\sigma_{CL} = -\frac{1}{\eta-1}$. Hypothesis tests of $\gamma = 1$ are rejected at the 5% significance level or lower.

The elasticity of steering time is positive but modest, ranging in [0.01,0.07]. We observe a slight bimodality: a subset of farms have near-zero change in S, while others exhibit somewhat higher elasticities. This suggests that some operators could be responding to the technology through modest increases in S, perhaps by expanding the total hours of field operations; this reflects a potential "expansion effect" that enables slightly more work time on the farm.[24] However, others keep their steering hours roughly constant, using autosteer to reallocate tasks without increasing field time. The net results is a small positive effect. The theory indicated that $(dS^*/d\alpha)$ is generally ambiguous: increasing α makes steering more productive, which encourages using the tractor more, but it also substitutes for other activities and faces diminishing returns. Our empirical result leans toward a positive effect, albeit one that is small.

5.4 Simulated Effects of Automation on Farm Household Income

Our baseline estimation assumes a relatively modest level of automation that reflects the time period of the dataset. But, what if the degree of automation increases (i.e., $\alpha \uparrow$)? To investigate this, we use the estimated model and comparative statics terms to: (1) simulate the impacts of autosteer use on farm household income in a benchmark scenario for which α increases from 0 to 0.30, and then (2) test the sensitivity of these simulations to changes in parameter assumptions. The results of the benchmark scenario are contained in the first row of Table 6, and the sensitivity results are shown in rows 2-8.

For the benchmark scenario, we assume operation i starts from its original values of the choice variables in the data, $\{S_{1i}, L_{1i}, W_{1i}, NW_{1i}, HL_{1i}\}$, which then change based on the estimated com-

[24] An acreage expansion effect is consistent with Griffin et al. (2005), who find that autosteer was profitable to US farmers during this period only when farm size could be increased.

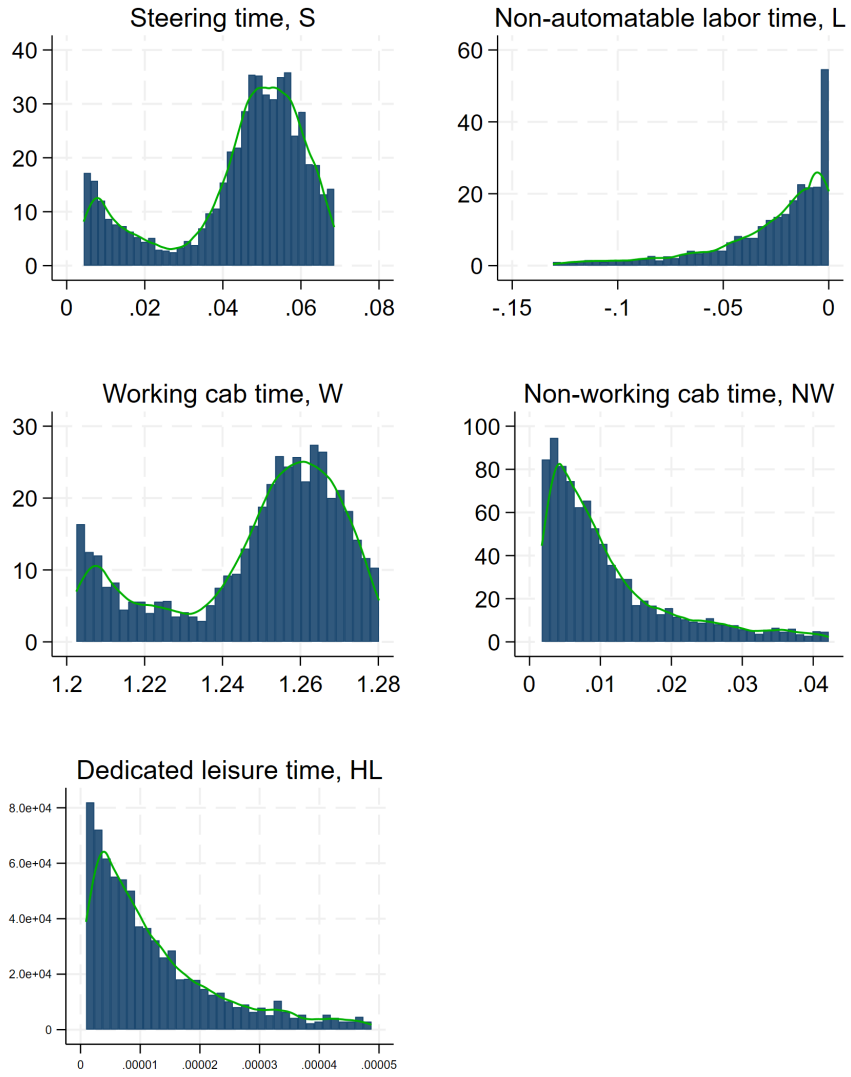


Figure 3: Estimated Elasticities for S, L, W, NW, and HL

parative statics, i.e., $\widetilde{X_{2i}} = X_{1i} \cdot \left(1 + \frac{d\hat{X}_i}{d\alpha}\right)$, where $\widetilde{X}_{2i} = \{\widetilde{S}_{2i}, \widetilde{L}_{2i}, \widetilde{W}_{2i}, \widetilde{NW}_{2i}, \widetilde{HL}_{2i}\}$. Note that since $NW = 0$ initially, we assume $\widetilde{NW}_{2i} = 0.001 \cdot (1 + \frac{d\hat{NW}_i}{d\alpha})$ in the automation scenario. The change in output is thus the difference, $Q_{2i} - Q_{1i}$, where

$$Q_{1i} = A_i \cdot \left(\hat{\theta}_1 S_{1i}^{\hat{\rho}} + \hat{\theta}_2 L_{1i}^{\hat{\rho}} + \hat{\theta}_3 Z_i^{\hat{\rho}} + \hat{\theta}_4 K_i^{\hat{\rho}}\right)^{(\hat{\gamma}/\hat{\rho})}$$
$$Q_{2i} = A_i \cdot \left(\hat{\theta}_1 S_{2i}^{\hat{\rho}} + \hat{\theta}_2 (L_{2i} + \hat{\alpha}\hat{\beta} S_{2i})^{\hat{\rho}} + \hat{\theta}_3 Z_i^{\hat{\rho}} + \hat{\theta}_4 K_i^{\hat{\rho}}\right)^{(\hat{\gamma}/\hat{\rho})}.$$

The change in variable input expenses as a result of automation is the reduction due to the mark-

Table 6: Simulation Results by Mechanism

		ΔHHI			Mechanism			
Result	**Statistic**	**Total % ΔHHI**	**Due to Farm Net Returns**	**Off-Farm Income**	**Only ΔS**	**Only ΔL**	**Only $\Delta R_Z Z$**	**Only ΔH_{off}**
Benchmark Comparative Static	Weighted Mean	9.80	8.51	1.27	0.13	−0.03	8.36	1.28
		(1.18)	(1.14)	(0.37)	(0.03)	(0.002)	(1.10)	(0.37)
	Winsorized Mean	5.70	4.65	0.79	0.08	−0.02	4.59	0.80
		(0.57)	(0.19)	(0.05)	(0.004)	(0.001)	(0.20)	(0.05)
Set $\alpha = 1$	Weighted Mean	9.65	8.51	1.12	0.13	−0.03	8.36	1.12
		(1.18)	(1.14)	(0.48)	(0.03)	(0.003)	(1.10)	(0.48)
	Winsorized Mean	5.69	4.64	0.79	0.07	−0.02	4.58	0.80
		(0.26)	(0.19)	(0.05)	(0.004)	(0.001)	(0.20)	(0.05)
Set $\beta = 0.15$	Weighted Mean	8.95	8.47	0.48	0.06	−0.01	8.36	0.48
		(1.13)	(1.14)	(0.23)	(0.01)	(0.001)	(1.10)	(0.23)
	Winsorized Mean	5.12	4.62	0.37	0.03	−0.01	4.58	0.37
		(0.23)	(0.19)	(0.03)	(0.002)	(0.003)	(0.20)	(0.03)
Assume $NW = 0.01 \cdot S$	Weighted Mean	9.29	6.86	2.27	0.07	−0.03	8.36	2.28
		(0.77)	(0.59)	(0.34)	(0.005)	(0.002)	(1.09)	(0.34)
	Winsorized Mean	6.06	4.27	1.03	0.05	−0.02	4.59	1.04
		(0.31)	(0.19)	(0.07)	(0.003)	(0.001)	(0.20)	(0.07)
CRS Production ($\gamma = 1$)	Weighted Mean	12.95	10.90	2.02	0.06	−0.01	10.74	2.03
		(1.77)	(1.66)	(0.66)	(0.01)	(0.004)	(1.61)	(0.66)
	Winsorized Mean	7.24	5.83	1.09	0.03	−0.004	5.77	1.09
		(0.26)	(0.25)	(0.06)	(0.002)	(0.0002)	(0.24)	(0.06)
More Input Complementarity ($\rho = 0.70$)	Weighted Mean	15.11	8.98	6.08	0.60	−0.26	8.65	6.13
		(4.78)	(1.72)	(5.15)	(0.15)	(0.05)	(1.63)	(5.14)
	Winsorized Mean	9.53	5.36	3.48	0.16	−0.10	5.23	3.51
		(0.42)	(0.22)	(0.24)	(0.01)	(0.01)	(0.20)	(0.24)
Less Consumption-Leisure Complementarity ($\eta = -1.5$)	Weighted Mean	13.22	11.18	2.02	0.14	−0.03	10.95	2.03
		(1.77)	(1.70)	(0.41)	(0.05)	(0.02)	(1.62)	(0.41)
	Winsorized Mean	6.79	5.59	0.91	0.05	−0.01	5.54	0.92
		(0.41)	(0.37)	(0.06)	(0.005)	(0.001)	(0.38)	(0.06)
Lower Cost Savings	Weighted Mean	9.04	7.75	1.27	0.13	−0.02	7.54	1.28
		(0.99)	(1.12)	(0.37)	(0.03)	(0.002)	(1.07)	(0.37)
	Winsorized Mean	5.18	4.00	0.79	0.07	−0.02	3.90	0.80
		(0.24)	(0.15)	(0.05)	(0.004)	(0.001)	(0.15)	(0.05)

Notes: Benchmark assumes (1) auto-steer has no extensive margin effects on off-farm hours, and (2) the change in variable costs relies on comparing fuel, seed, fertilizer, and chemical per-acre costs (for years 2001–03) for adopters vs. non-adopters, using winsorization and dropping cotton from the chemical calculation. Means and winsorized means are weighted using survey expansion factors from NASS. Winsorization is at the 5th and 95th percentiles. Delete-a-group jackknife standard errors are in parentheses. "Lower cost savings" follows assumptions from Shockley et al. (2011).

down, $\hat{\tau}$. Thus, the change in net returns on operation i due to this automation scenario is $[PQ_{2i} - \hat{\tau} R_Z Z_i] - [PQ_{1i} - R_Z Z_i]$. Likewise, the new level of off-farm work hours for operation i is $H_{2i,off} = \bar{T}_i - \widetilde{S}_{2i} - \widetilde{L}_{2i} - \widetilde{HL}_{2i}$, implying the change in off-farm income is $R_H \cdot (H_{2i,off} - H_{1i,off})$.

The results indicate that autosteer use would raise total farm household income by about 9.8% on average (using the weighted mean) in this baseline scenario. This gain is driven predominantly by higher farm net returns, which increase by roughly 8.5%, while off-farm income rises by about 1.3%. In other words, improved on-farm profitability accounts for the majority of the household income boost (approximately 87% of the total percentage gain), with the remainder coming from a modest increase in off-farm earnings. By construction, the sum of the percent change in net farm returns (8.5%) and the percent change in off-farm income (1.3%) equals the overall 9.8% increase in household income, and this decomposition holds consistently across the various channels of impact.

The simulation attributes the farm income gains to specific mechanisms in the model, and their contributions collectively sum to the total impact. The 8.5% rise in farm net returns reflects two main effects of autosteer. First, autosteer improves productivity and output (Q) by allowing more effective use of labor and equipment; for example, some of the operator's field work can be done more efficiently (the production function effectively gains a term $\alpha\beta S$ that augments labor). Second, autosteer reduces production costs via a cost markdown on variable inputs (since $\tau > 0$

when $\alpha > 0$). Together, these effects boost farm revenue and lower costs (asymmetrically), raising net returns. In terms of the model's decision variables, we observe that automation leads to a reallocation of labor: manual labor requirements (L) decline (since steering tasks can be performed more efficiently by the machine/operator combination), and the operator's multi-taskable labor time (S) may be re-optimized (potentially not increasing much due to diminishing returns in labor use). The reduction in manual labor and more precise input use (reflected in the $R_Z Z$ term) translate into lower costs, while greater effective labor input raises output; both effects contribute positively to net returns. At the same time, farm operators adjust their off-farm work hours. Because on-farm tasks can be completed with less manual effort (time), the household allocates slightly more time to off-farm employment, yielding the 1.3% increase in off-farm income. This off-farm labor response, though relatively small, indicates that some of the time savings from autosteer are diverted to earning wages outside the farm.

The remaining rows of Table 6 examine how sensitive these results are to alternative parameter assumptions. We simulate the same increase in automation but adjust key parameters, such as those for input substitution, the magnitude of the autosteer productivity effect (β), the cost markdown factor (τ), and the off-farm wage rate. Across all of these scenarios, autosteer adoption consistently increases farm net returns more than off-farm income, as expected, though magnitude of these gains varies with the assumptions. The size of the income changes tend to deviate from the benchmark by up to 5 percentage points, with most assumption changes having only minor effects. For instance, in scenarios where autosteer's benefits are assumed to be more limited, such as a smaller productivity boost ($\beta = 0.15$) or lower cost savings, household income rises by a smaller percentage (though still on the order of several percent). In contrast, under assumptions that amplify autosteer's advantages (for example, a production function with CRS), the income gain is somewhat larger.

As expected, the parameters with the greatest impact on the simulations are the production function's degree of homogeneity and the substitution parameters in both the utility and production function. When γ increases to 1, the output elasticity with respect to inputs rises, so the productivity boost from autosteer leads to a larger increase in output than under diminishing returns. Additionally, because autosteer now frees more economically valuable time, households shift more hours to off-farm work, raising off-farm income. Under greater input complementarity ($\rho = 0.70$) the four productive inputs are less easily substitutable, so additional labor on the farm has sharply diminishing returns unless accompanied by more of the other inputs. In this scenario, the household finds it more profitable to reallocate labor off-farm, where a fixed wage can be earned. As a result, off-farm income increases from 1.27 to 6.08, i.e., the household is willing to shift much of its work effort to off-farm employment when farm labor can less effectively increase output. Last, with less consumption-leisure complementarity ($\eta = -1.5$), consumption and leisure become more substitutable in the utility function. The household is more willing to trade off leisure for consumption, i.e., they will work longer hours when it is beneficial to maintain or increase consumption. This change in preferences would be consistent with behavior under adverse shocks or new opportunities in which the household would sacrifice more leisure in favor of labor, again boosting off-farm work

and overall income.

5.5 Discussion

Our empirical findings highlight how labor-saving technology in agriculture can reshape intrahousehold labor allocation and improve economic well-being. In this case, autosteer effectively augments the farm household's labor supply by enabling multitasking and freeing up time for other uses. Importantly, the benefits of autosteer manifest not in increased leisure for the farm operator, but in higher productive labor both on and off the farm. The farmer continues to work roughly the same hours, but with autosteer, they can accomplish more during those hours and with slightly less manual effort. At the same time, the farmer is able to reallocate some labor to off-farm employment, indicating a classic sectoral shift of labor at the household level: time saved on the farm is re-invested into the off-farm labor market. This pattern is consistent with a stylized fact underlying many studies that technological progress allows for a release of labor to other productive uses (e.g., Whatley, 1985; Foster and Rosenzweig, 2007; Alston and Pardey, 2014). Here we see it on a seasonal household scale as autosteer adoption leads the farmer to diversify its labor portfolio, increasing off-farm work slightly without sacrificing farm output.

The result is a boost to household income without a reduction in leisure, suggesting that farm households value the added income strongly to further bolster consumption. The lack of increased leisure reflects the complementary relationship between leisure and consumption in utility; additional free time has relatively lower marginal utility unless the farmer has resources to enjoy it. Thus, given the choice, these households channel the benefits of automation into earnings. In essence, autosteer raises the effective labor productivity of the farm household, which in turn raises their material well-being. Notably, the gains are driven mostly by cost reductions rather than pure labor hours expansion, implying they reflect productivity improvements. The farmer's work is made less arduous and more efficient, if not shorter, and the household gains financially as a result.

In terms of labor supply, the effective increase in available working time via multitasking can be viewed similarly to an increase in the farmer's human capital (e.g., Huffman, 1980). The operator can essentially be in two places at once, managing the tractor and handling other work simultaneously. Importantly, this is likely to improve quality of life in less tangible ways, i.e., the nature of equipment-related work becomes less physically demanding. Many farmers likely derive utility from reduced stress and/or being able to accomplish more in a day. Even when quantity of leisure does not increase much, the quality of leisure time may be higher quality due to less fatigue and work distraction. Such qualitative benefits are harder to measure but likely accompany the quantitative gains we estimate.

Our results demonstrate that automation in agriculture, even in a context of partial automation like autosteer, can have meaningful economic payoffs and lead to a reorganization of household labor. Autosteer is a productivity-enhancing tool that farm households leverage to improve their economic well-being, principally by saving costs on the farm and reallocating time to additional remunerative work. As automation deepens in the coming years, we would expect the aggregate

effects to be increases in both farm efficiency and off-farm labor supply in farming regions, in addition to improved quality of life through lower fatigue and physical stress.

6 Conclusion

This paper develops and estimates a farm household production model to assess the effects of a key automation technology (specifically, GPS-based autosteer) on U.S. farm household time use and income. Using detailed, nationally representative microdata from USDA's Agricultural Resource Management Survey (ARMS), we construct a pooled field- and enterprise-level dataset that allows us to model the economic implications of autosteer adoption. The structural model incorporates multitasking constraints and automation-enabled time reallocation, novel features that were not previously incorporated into empirical work within this literature. Using a control function approach that addresses model-based sources of endogeneity, our results show that autosteer adoption leads to small but economically meaningful increases in total household income. This increase is driven largely by improvements in farm productivity and reductions in variable input costs, as well as modest shifts in operator time toward more productive uses including off-farm work.

Simulation exercises using our estimated model suggest that autosteer increases farm household income by approximately 8-9% on average, with the vast majority of gains coming from increased net returns to farming. Increases in off-farm income account for about 1-2% of the total gain, reflecting the model's prediction that freed-up time is modestly reallocated to off-farm labor. Elasticity estimates reveal that most freed-up steering time is used for productive multitasked work within the equipment cab rather than for leisure, consistent with the estimated complementarity between consumption and leisure. We find little change in dedicated leisure or non-automated work tasks (e.g., manual labor), suggesting limited substitution across time uses. These results are robust across a range of sensitivity checks, though the magnitude of household income gains varies somewhat with the degree of complementarity among goods in the household utility function and agricultural production function, as well as returns to scale in production.

Several limitations are worth noting. First, our empirical strategy relies on approximations to marginal rate of substitution parameter derived from external data sources that do not completely match the time and setting of our application. As such, this mismatch may not fully reflect the productivity of multitasked time in current US crop production. Second, the analysis relies on data from the early 2000s, a period when autosteer technology was in its infancy. The agricultural landscape has evolved substantially since time with more than half of major U.S. field crop acreage now being managed with guidance systems; thus, our estimates capture the impact on early adopters. Third, the empirical methods struggled to precisely estimate certain input share parameters, although such issues could be resolved with certain model reformulations. Fourth, as with most studies in this literature, unobserved factors could still influence both technology adoption and our production and income outcomes of interest despite our control function approach.

Our study points to several directions for future research. Refining the household production

model to better capture multitasking and time-use tradeoffs could deepen our understanding of how automation impacts farm family welfare. It could also be fruitful to extend the analysis to emerging automation technologies in agriculture. Autosteer was one of the first rapidly and widely adopted precision farming tools and has transformed how farmers perform planting and harvest operations. However, newer innovations (e.g., drone-assisted operations, precision pest management, and fully autonomous tractors) are becoming part of modern farm management. As these technologies diffuse, their economic effects may resemble those experienced by early autosteer adopters, potentially further transforming labor requirements and productivity in agriculture. In a broader context, understanding the diffusion of farm automation is critical for anticipating changes in rural labor markets and farm household livelihoods. Our findings contribute to this understanding by documenting that a partial automation tool, such as autosteer, can deliver measurable income benefits and subtle shifts in labor allocation even in the technology's early years. Further, the quality-of-life benefits from automation may play a pivotal role in sustaining the agricultural workforce by making farming more attractive to new entrants and retaining existing producers (Campi et al., 2024). Continued research at the intersection of technology adoption, farm productivity, and time use will be important for informing both policymakers and farm managers about the human resource implications of technological progress.

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A Full Model & Derivations

The Lagrangian for the optimization problem provided in (7) is copied below for ease of access:

$$\mathcal{L} = \left[\delta\Big(P\cdot A\cdot X_P^{\gamma} - \tau R_Z Z + R_H H_{off} + V - B\Big)^{\eta} + (1-\delta)\, X_U^{\eta}\right]^{\frac{\psi}{\eta}} + \lambda_1\left[\bar{T} - S - L - H_{off} - HL\right] + \lambda_2\left[\alpha S - W - NW\right] \quad \text{(A.1)}$$

where the CES aggregators and total leisure identity are defined as:

- $X_P \equiv (\theta_1 S^{\rho} + \theta_2(L+\beta W)^{\rho} + \theta_3 Z^{\rho} + \theta_4 K^{\rho})^{\frac{1}{\rho}}$
- $X_U = HL + \phi NW.$

Differentiating with respect to the five decision variables (S, L, W, NW, HL) and assuming an interior solution yields the FONCs:

$$\frac{\partial \mathcal{L}}{\partial S} = M_1 \cdot M_2 \cdot M_3 \cdot \theta_1 \rho S^{\rho-1} - \lambda_1 + \lambda_2 \alpha = 0 \quad \text{(A.2)}$$

$$\frac{\partial \mathcal{L}}{\partial L} = M_1 \cdot M_2 \cdot M_3 \cdot \theta_2 \rho (L+\beta W)^{\rho-1} - \lambda_1 = 0 \quad \text{(A.3)}$$

$$\frac{\partial \mathcal{L}}{\partial W} = M_1 \cdot M_2 \cdot M_3 \cdot \theta_2 \rho (L+\beta W)^{\rho-1}\beta - \lambda_2 = 0 \quad \text{(A.4)}$$

$$\frac{\partial \mathcal{L}}{\partial NW} = M_1 \cdot M_4 \cdot \phi - \lambda_2 = 0 \quad \text{(A.5)}$$

$$\frac{\partial \mathcal{L}}{\partial HL} = M_1 \cdot M_4 - \lambda_1 = 0 \quad \text{(A.6)}$$

where we define:

$$M_1 = \frac{\psi}{\eta}\left(\delta(PAX_P^{\gamma} + R_H H_{off} + V - \tau R_Z Z - B)^{\eta} + (1-\delta)X_U^{\eta}\right)^{\frac{\psi}{\eta}-1} \quad \text{(A.7)}$$

$$M_2 = \delta\eta(PAX_P^{\gamma} + R_H H_{off} + V - \tau R_Z Z - B)^{\eta-1} \quad \text{(A.8)}$$

$$M_3 = PA\left(\frac{\gamma}{\rho}\right) X_P^{\gamma-\rho} \quad \text{(A.9)}$$

$$M_4 = (1-\delta)\eta X_U^{\eta-1} \quad \text{(A.10)}$$

The ratios $\frac{(11)}{(12)}$ and $\frac{(10)}{(9)}$ imply the equality of the marginal rate of the substitution parameters:

$$\phi = \beta. \quad \text{(A.11)}$$

The ratio, $\frac{(8)}{(9)}$, together with $\phi = \frac{\lambda_2}{\lambda_1}$, which comes from the ratio $\frac{(11)}{(12)}$, implies:

$$S = \left[\frac{\theta_2}{\theta_1}(1-\alpha\phi)\right]^{\frac{1}{\rho-1}} \cdot (L+\beta W). \quad \text{(A.12)}$$

Similarly, from $\frac{(8)}{(11)}$:

$$M_4 = M_2 \cdot M_3 \cdot \theta_1 \rho S^{\rho-1}\left(\frac{1}{1-\alpha\phi}\right). \quad \text{(A.13)}$$

Substituting expressions for M_2 (A.8), M_3 (A.9), and M_4 (A.10) into (A.13) and isolating for X_U on the left-hand side:

$$X_U = \left[\frac{\delta}{1-\delta} PA\gamma \frac{\theta_1}{1-\alpha\phi}\right]^{\frac{1}{\eta-1}} S^{\frac{\rho-1}{\eta-1}} (PAX_P^{\gamma} + R_H H_{off} + V - \tau R_Z Z - B) X_P^{\frac{\gamma-\rho}{\eta-1}}. \quad \text{(A.14)}$$

Substituting $X_U = HL + \phi NW$ and $\beta = \phi$:

$$HL + \beta NW = \left[\frac{\delta}{1-\delta}\frac{PA\gamma\theta_1}{1-\alpha\beta}\right]^{\frac{1}{\eta-1}} S^{\frac{\rho-1}{\eta-1}} \left(\underbrace{PAX_P^{\gamma} + R_H H_{off} + V - \tau R_Z Z - B}_{C}\right) X_P^{\frac{\gamma-\rho}{\eta-1}}. \quad \text{(A.15)}$$

$$HL + \beta NW = \left[\frac{\delta}{1-\delta}\frac{PA\gamma\theta_1}{1-\alpha\beta}\right]^{\frac{1}{\eta-1}} S^{\frac{\rho-1}{\eta-1}} \cdot C \cdot X_P^{\frac{\gamma-\rho}{\eta-1}}.$$

Taking logs of both sides yields the following:

$$\ln(HL + \beta NW) = \frac{1}{\eta - 1} \ln\left[\frac{\delta}{1-\delta}\frac{PA\gamma\theta_1}{1-\alpha\beta}\right] + \frac{\rho - 1}{\eta - 1}\ln(S) + \ln(C) + \frac{\gamma - \rho}{\eta - 1}\ln(X_P).$$

Next, isolating variables:

$$\begin{aligned}\ln(HL) + \ln\left(1 + \beta\frac{NW}{HL}\right) = {} & \frac{1}{\eta - 1}\ln\left(\frac{\delta}{1-\delta}\right) + \frac{1}{\eta - 1}\ln(\theta_1) + \frac{1}{\eta - 1}\ln\left(\frac{\gamma}{1-\alpha\beta}\right) + \frac{1}{\eta - 1}\ln(A) + \frac{1}{\eta - 1}\ln(P) \\ & + \frac{\rho - 1}{\eta - 1}\ln(S) + \ln(C) + \frac{\gamma - \rho}{\eta - 1}\ln(X_P).\end{aligned} \tag{A.16}$$

Rearranging terms and assuming NW ≈ 0:

$$\begin{aligned}\ln(HL) - \ln(C) = {} & \underbrace{\frac{1}{\eta - 1}\ln\left(\frac{\delta}{1-\delta}\right)}_{Constant} + \frac{1}{\eta - 1}\ln(\theta_1) + \frac{1}{\eta - 1}\ln\left(\frac{\gamma}{1-\alpha\beta}\right) + \frac{1}{\eta - 1}\ln(A) + \frac{1}{\eta - 1}\ln(P) \\ & + \frac{\rho - 1}{\eta - 1}\ln(S) + \frac{\gamma - \rho}{\eta - 1}\ln(X_P) - \underbrace{\ln\left(1 + \beta\frac{NW}{HL}\right)}_{\approx 0}.\end{aligned} \tag{A.17}$$

Substituting in $X_P = \left(\frac{Q}{A}\right)^{\frac{1}{\gamma}}$ and combining the terms for $\ln(A)$ gives:

$$\begin{aligned}\ln(HL) - \ln(C) = {} & Constant + \frac{1}{\eta - 1}\ln(\theta_1) + \frac{1}{\eta - 1}\ln\left(\frac{\gamma}{1-\alpha\beta}\right) + \frac{\rho}{\gamma(\eta - 1)}\ln(A) + \frac{1}{\eta - 1}\ln(P) \\ & + \frac{\rho - 1}{\eta - 1}\ln(S) + \frac{\gamma - \rho}{\gamma(\eta - 1)}\ln(Q).\end{aligned} \tag{A.18}$$

Substituting for Q as defined in (3) and appending an econometric error term (ϵ), yields:

$$\begin{aligned}\ln(HL) - \ln(C) = {} & Constant + \frac{1}{\eta - 1}\ln(\theta_1) + \frac{1}{\eta - 1}\ln\left(\frac{\gamma}{1-\alpha\beta}\right) + \frac{\rho}{\gamma(\eta - 1)}\ln(A) + \frac{1}{\eta - 1}\ln(P) + \frac{\rho - 1}{\eta - 1}\ln(S) \\ & + \frac{\gamma - \rho}{\gamma(\eta - 1)}\left[\ln(A) + \frac{\gamma}{\rho}\ln\left(\theta_1 S^\rho + \theta_2(L + \beta\alpha S)^\rho + \theta_3 Z^\rho + \theta_4 K^\rho\right)\right] + \epsilon.\end{aligned} \tag{A.19}$$

Finally, we combine like terms and add generalized residuals into the production function to correct for potential endogeneity of steering (GR_S) and labor (GR_L) time to yield the following equation:

$$\begin{aligned}\ln(HL) - \ln(C) = {} & Constant + \frac{1}{\eta - 1}\ln(\theta_1) + \frac{1}{\eta - 1}\ln\left(\frac{\gamma}{1-\alpha\beta}\right) + \frac{1}{\eta - 1}\ln(A) + \frac{1}{\eta - 1}\ln(P) + \frac{\rho - 1}{\eta - 1}\ln(S) \\ & + \frac{\gamma - \rho}{\rho(\eta - 1)}\left[\ln\left(\theta_1 S^\rho + \theta_2(L + \beta\alpha S)^\rho + \theta_3 Z^\rho + \theta_4 K^\rho + \xi_S GR_S + \xi_L GR_L\right)\right] + \epsilon.\end{aligned} \tag{A.20}$$

Note that the parameters must meet the following five standard restrictions: 1) $\theta_1, \theta_2, \theta_3, \theta_4 \in [0, 1]$, 2) $\sum_{j=1}^{4}\theta_j = 1$, 3) $\rho < 1$, 4) $\eta < 1$, and $\gamma > 0$. To impose these restrictions, we incorporate the following reparameterizations when estimating the model:

- $\theta_1 = \frac{1}{1+\sum_{j=2}^{4}\exp(t_j)}$
- $\theta_2 = \frac{\exp(t_2)}{1+\sum_{j=2}^{4}\exp(t_j)}$
- $\theta_3 = \frac{\exp(t_3)}{1+\sum_{j=2}^{4}\exp(t_j)}$
- $\theta_4 = \frac{\exp(t_4)}{1+\sum_{j=2}^{4}\exp(t_j)}$
- $\rho = 1 - \exp(d_1)$
- $\eta = 1 - \exp(e_1)$

- $\gamma = \exp(g_1)$.

We thus estimate $\{t_2, t_3, t_4\}, d_1, e_1$ and g_1 and use the above transformations to calculate the parameters of interest. We see from the above expressions that:

- $\hat{t}_2 = \ln\left(\frac{\hat{\theta}_2}{\hat{\theta}_1}\right)$
- $\hat{t}_3 = \ln\left(\frac{\hat{\theta}_3}{\hat{\theta}_1}\right)$
- $\hat{t}_4 = \ln\left(\frac{\hat{\theta}_4}{\hat{\theta}_1}\right)$
- $\hat{d}_1 = \ln\left(1 - \hat{\rho}\right)$
- $\hat{e}_1 = \ln\left(1 - \hat{\eta}\right)$
- $\hat{g}_1 = \ln\left(\hat{\gamma}\right)$

B Comparative Statics

For comparative statics, we rewrite the optimization problem in (7) by substituting out H_{off} using the time constraint (5) and W using the multi-tasking constraint (6):

$$\mathcal{L} = \left[\delta\Big(PAX_P^{\gamma} + R_H(\bar{T} - S - L - HL) + V - \tau R_Z Z - B\Big)^{\eta} + (1-\delta)X_U^{\eta}\right]^{\frac{\psi}{\eta}} \tag{B.1}$$

where the CES aggregators and total leisure identity are defined as:

$$X_P \equiv (\theta_1 S^{\rho} + \theta_2(L + \alpha\beta S - \beta NW)^{\rho} + \theta_3 Z^{\rho} + \theta_4 K^{\rho})^{\frac{1}{\rho}}, \quad X_U \equiv HL + \phi NW.$$

Deriving first-order necessary conditions yields:

$$\frac{\partial \mathcal{L}}{\partial S} = M_1 M_2(M_3 M_{F1} - R_H) = 0 = F_1 \tag{B.2}$$

$$\frac{\partial \mathcal{L}}{\partial L} = M_1 M_2(M_3 M_{F2} - R_H) = 0 = F_2 \tag{B.3}$$

$$\frac{\partial \mathcal{L}}{\partial NW} = M_1(M_2 M_3 M_{F2}(-\beta) + M_4\phi) = 0 = F_3 \tag{B.4}$$

$$\frac{\partial \mathcal{L}}{\partial HL} = M_1(-M_2 R_H + M_4) = 0 = F_4 \tag{B.5}$$

with terms defined as:

$$M_1 = \frac{\psi}{\eta}\left[\delta(PAX_P^{\gamma} + R_H(\bar{T} - S - L - HL) + V - \tau R_Z Z - B)^{\eta} + (1-\delta)X_U^{\eta}\right]^{\frac{\psi}{\eta}-1} = \frac{\psi}{\eta}\left[\delta C^{\eta} + (1-\delta)X_U^{\eta}\right]^{\frac{\psi}{\eta}-1} \tag{B.6}$$

$$M_2 = \delta\eta(PAX_P^{\gamma} + R_H(\bar{T} - S - L - HL) + V - \tau R_Z Z - B)^{\eta-1} = \delta\eta C^{\eta-1} \tag{B.7}$$

$$M_3 = PA\left(\frac{\gamma}{\rho}\right)X_P^{\gamma-\rho} \tag{B.8}$$

$$M_4 = (1-\delta)\eta X_U^{\eta-1} \tag{B.9}$$

$$M_{F1} = \theta_1\rho S^{\rho-1} + \theta_2\rho(L + \alpha\beta S - \beta NW)^{\rho-1}\alpha\beta \tag{B.10}$$

$$M_{F2} = \theta_2\rho(L + \alpha\beta S - \beta NW)^{\rho-1} \tag{B.11}$$

We also define two frequently used terms:

$$\aleph_1 \equiv \theta_2\rho(L + \alpha\beta S - \beta NW)^{\rho-1} \cdot \beta S \tag{B.12}$$

$$\aleph_2 \equiv \theta_2\rho(L + \alpha\beta S - \beta NW)^{\rho-1} \cdot \alpha\beta + \theta_1\rho S^{\rho-1} \tag{B.13}$$

Next, we derive comparative statics with respect to α using each FONC explicitly:

$$\frac{dS^*}{d\alpha} = -\frac{\frac{\partial F_1}{\partial \alpha}}{\frac{\partial F_1}{\partial S^*}}, \quad \frac{dL^*}{d\alpha} = -\frac{\frac{\partial F_2}{\partial \alpha}}{\frac{\partial F_2}{\partial L^*}}, \quad \frac{dNW^*}{d\alpha} = -\frac{\frac{\partial F_3}{\partial \alpha}}{\frac{\partial F_3}{\partial NW^*}}, \quad \text{and } \frac{dHL^*}{d\alpha} = -\frac{\frac{\partial F_4}{\partial \alpha}}{\frac{\partial F_4}{\partial HL^*}}$$

The detailed versions of the comparative statics (with respect to α) from each FONC are:

$$\frac{dS^*}{d\alpha} = -\frac{\left[\frac{\partial M_1}{\partial \alpha}\left(\frac{1}{M_1}\right) + \frac{\partial M_2}{\partial \alpha}\left(\frac{1}{M_2}\right) + \frac{\partial M_3}{\partial \alpha}\left(\frac{1}{M_3}\right) + \frac{\partial M_{F1}}{\partial \alpha}\left(\frac{1}{M_{F1}}\right)\right] - R_H\frac{\partial M_2}{\partial \alpha}\cdot\left(\frac{1}{M_2 M_3 M_{F1}}\right) - R_H\frac{\partial M_1}{\partial \alpha}\cdot\left(\frac{1}{M_1 M_3 M_{F1}}\right)}{\left[\frac{\partial M_1}{\partial S^*}\left(\frac{1}{M_1}\right) + \frac{\partial M_2}{\partial S^*}\left(\frac{1}{M_2}\right) + \frac{\partial M_3}{\partial S^*}\left(\frac{1}{M_3}\right) + \frac{\partial M_{F1}}{\partial S^*}\left(\frac{1}{M_{F1}}\right)\right] - R_H\frac{\partial M_2}{\partial S^*}\cdot\left(\frac{1}{M_2 M_3 M_{F1}}\right) - R_H\frac{\partial M_1}{\partial S^*}\cdot\left(\frac{1}{M_1 M_3 M_{F1}}\right)} \tag{B.14}$$

$$\frac{dL^*}{d\alpha} = -\frac{\left[\frac{\partial M_1}{\partial \alpha}\left(\frac{1}{M_1}\right) + \frac{\partial M_2}{\partial \alpha}\left(\frac{1}{M_2}\right) + \frac{\partial M_3}{\partial \alpha}\left(\frac{1}{M_3}\right) + \frac{\partial M_{F2}}{\partial \alpha}\left(\frac{1}{M_{F2}}\right)\right] - R_H\frac{\partial M_2}{\partial \alpha}\cdot\left(\frac{1}{M_2 M_3 M_{F2}}\right) - R_H\frac{\partial M_1}{\partial \alpha}\cdot\left(\frac{1}{M_1 M_3 M_{F2}}\right)}{\left[\frac{\partial M_1}{\partial L^*}\left(\frac{1}{M_1}\right) + \frac{\partial M_2}{\partial L^*}\left(\frac{1}{M_2}\right) + \frac{\partial M_3}{\partial L^*}\left(\frac{1}{M_3}\right) + \frac{\partial M_{F2}}{\partial L^*}\left(\frac{1}{M_{F2}}\right)\right] - R_H\frac{\partial M_2}{\partial L^*}\cdot\left(\frac{1}{M_2 M_3 M_{F2}}\right) - R_H\frac{\partial M_1}{\partial L^*}\cdot\left(\frac{1}{M_1 M_3 M_{F2}}\right)} \tag{B.15}$$

$$\frac{dNW^*}{d\alpha} = -\frac{\left[\frac{\partial M_1}{\partial \alpha}\left(\frac{1}{M_1}\right) + \frac{\partial M_2}{\partial \alpha}\left(\frac{1}{M_2}\right) + \frac{\partial M_3}{\partial \alpha}\left(\frac{1}{M_3}\right) + \frac{\partial M_{F2}}{\partial \alpha}\left(\frac{1}{M_{F2}}\right)\right] + \phi\left(M_4\frac{\partial M_1}{\partial \alpha}\right)\cdot\left(\frac{1}{-\beta M_1 M_2 M_3 M_{F2}}\right)}{\left[\frac{\partial M_1}{\partial NW^*}\left(\frac{1}{M_1}\right) + \frac{\partial M_2}{\partial NW^*}\left(\frac{1}{M_2}\right) + \frac{\partial M_3}{\partial NW^*}\left(\frac{1}{M_3}\right) + \frac{\partial M_{F2}}{\partial NW^*}\left(\frac{1}{M_{F2}}\right)\right] + \phi\left(M_1\cdot\frac{\partial M_4}{\partial NW^*} + M_4\frac{\partial M_1}{\partial NW^*}\right)\cdot\left(\frac{1}{-\beta M_1 M_2 M_3 M_{F2}}\right)} \tag{B.16}$$

$$\frac{dHL^*}{d\alpha} = -\frac{-R_H \cdot M_1 \cdot \frac{\partial M_2}{\partial \alpha} + \frac{\partial M_1}{\partial \alpha}(M_4 - R_H \cdot M_2)}{M_1\left(\frac{\partial M_4}{\partial HL^*} - R_H \frac{\partial M_2}{\partial HL^*}\right) + \frac{\partial M_1}{\partial HL^*}(M_4 - R_H \cdot M_2)} \tag{B.17}$$

Each of the first two comparative static expressions (e.g., $\frac{dS^*}{d\alpha}$) takes the form:

$$\frac{dS^*}{d\alpha} = -\frac{[\text{sum of derivatives w.r.t. } \alpha] - R_H \cdot \text{wage adjustment terms}}{[\text{sum of derivatives w.r.t. } S^*] - R_H \cdot \text{wage adjustment terms}}$$

For example, a square-bracketed term like

$$\left[\frac{\partial M_1}{\partial \alpha}\left(\frac{1}{M_1}\right) + \frac{\partial M_2}{\partial \alpha}\left(\frac{1}{M_2}\right) + \frac{\partial M_3}{\partial \alpha}\left(\frac{1}{M_3}\right) + \frac{\partial M_{F1}}{\partial \alpha}\left(\frac{1}{M_{F1}}\right)\right]$$

represents the normalized responsiveness of each FONC component to α.

Each individual derivative (e.g., $\frac{\partial M_3}{\partial \alpha} \cdot \frac{1}{M_3}$) captures the elasticity or relative sensitivity of a marginal product or utility with respect to automation (α) or to a decision variable such as S, L, etc. These are second-order marginal effects: they measure how automation changes the marginal benefit of allocating more time to a particular use.

For an example of a term-by-term interpretation, consider:

- M_1: Derivative of CES utility: reflects how utility changes with consumption and time allocation.
- M_2: Marginal utility of consumption: a direct component of the utility gradient in the Lagrangian.
- M_3: Marginal product of the CES production aggregator: an analog of a production marginal product.
- M_{F1}, M_{F2}: Partial derivatives of the production function with respect to S and L: these are the marginal products of auto-steering time and manual labor, respectively.

Thus, the numerator bracketed terms like $[\cdot]_\alpha$ capture how marginal benefits (utility or productivity) respond to automation. The denominator bracketed terms like $[\cdot]_{S^*}$ or $[\cdot]_{L^*}$ reflect how those same marginal benefits respond to a change in the choice variable — these can be interpreted as curvature effects or slopes of marginal benefit schedules. More broadly, the bracketed expressions can be interpreted as weighted sums of marginal products and marginal utilities, scaled by their responsiveness to automation or time allocation, representing how profitable or desirable additional effort becomes under a change in α.

The partial derivatives needed for the four comparative statics terms are:

$$\frac{\partial M_1}{\partial \alpha}\left(\frac{1}{M_1}\right) = \left(\frac{\psi}{\eta} - 1\right)\frac{\delta\eta(PAX_P^\gamma + R_H(\bar{T} - S - L - HL) + V - \tau R_Z Z - B)^{\eta-1} \cdot PA\frac{\gamma}{\rho}X_P^{\gamma-\rho} \cdot \aleph_1}{\delta(PAX_P^\gamma + R_H(\bar{T} - S - L - HL) + V - \tau R_Z Z - B)^\eta + (1-\delta)X_U^\eta} \tag{B.18}$$

$$\frac{\partial M_2}{\partial \alpha}\left(\frac{1}{M_2}\right) = (\eta - 1)\frac{PA\frac{\gamma}{\rho}X_P^{\gamma-\rho} \cdot \aleph_1}{PAX_P^\gamma + R_H(\bar{T} - S - L - HL) + V - \tau R_Z Z - B} \tag{B.19}$$

$$\frac{\partial M_3}{\partial \alpha}\left(\frac{1}{M_3}\right) = \left(\frac{\gamma}{\rho} - 1\right)\frac{\aleph_1}{X_P^\rho} \tag{B.20}$$

$$\frac{\partial M_{F1}}{\partial \alpha}\left(\frac{1}{M_{F1}}\right) = \frac{\aleph_1}{\aleph_2}\left[\frac{1}{S} + \frac{\alpha\beta(\rho-1)}{(L + \alpha\beta S - \beta NW)}\right] \tag{B.21}$$

$$\frac{\partial M_{F2}}{\partial \alpha}\left(\frac{1}{M_{F2}}\right) = (\rho - 1)\frac{\beta S}{L + \alpha\beta S - \beta NW} \tag{B.22}$$

$$\frac{\partial M_1}{\partial S^*}\left(\frac{1}{M_1}\right) = \left(\frac{\psi}{\eta} - 1\right)\frac{\delta\eta(PAX_P^\gamma + R_H(\bar{T} - S - L - HL) + V - \tau R_Z Z - B)^{\eta-1}\left[PA\frac{\gamma}{\rho}X_P^{\gamma-\rho}\aleph_2 - R_H\right]}{\delta(PAX_P^\gamma + R_H(\bar{T} - S - L - HL) + V - \tau R_Z Z - B)^\eta + (1-\delta)X_U^\eta} \tag{B.23}$$

$$\frac{\partial M_2}{\partial S^*}\left(\frac{1}{M_2}\right) = (\eta - 1)\frac{PA\frac{\gamma}{\rho}X_P^{\gamma-\rho}\aleph_2 - R_H}{PAX_P^\gamma + R_H(\bar{T} - S - L - HL) + V - \tau R_Z Z - B} \tag{B.24}$$

$$\frac{\partial M_3}{\partial S^*}\left(\frac{1}{M_3}\right) = \left(\frac{\gamma}{\rho} - 1\right)\frac{\aleph_2}{X_P^\rho} \tag{B.25}$$

$$\frac{\partial M_{F1}}{\partial S^*}\left(\frac{1}{M_{F1}}\right) = \frac{\rho - 1}{\aleph_2}\left(\theta_1\rho S^{\rho-2} + \frac{\aleph_1\alpha^2\beta}{(L + \alpha\beta S - \beta NW)S}\right) \tag{B.26}$$

$$\frac{\partial M_1}{\partial L^*}\left(\frac{1}{M_1}\right) = \left(\frac{\psi}{\eta} - 1\right)\frac{\delta\eta(PAX_P^{\gamma} + R_H(\bar{T} - S - L - HL) + V - \tau R_Z Z - B)^{\eta-1}\left(PA\frac{\gamma}{\rho}X_P^{\gamma-\rho}\frac{\aleph_1}{\beta S} - R_H\right)}{\delta(PAX_P^{\gamma} + R_H(\bar{T} - S - L - HL) + V - \tau R_Z Z - B)^{\eta} + (1-\delta)X_U^{\eta}} \tag{B.27}$$

$$\frac{\partial M_2}{\partial L^*}\left(\frac{1}{M_2}\right) = (\eta - 1)\frac{PA\frac{\gamma}{\rho}X_P^{\gamma-\rho}\frac{\aleph_1}{\beta S} - R_H}{PAX_P^{\gamma} + R_H(\bar{T} - S - L - HL) + V - \tau R_Z Z - B} \tag{B.28}$$

$$\frac{\partial M_3}{\partial L^*}\left(\frac{1}{M_3}\right) = \left(\frac{\gamma}{\rho} - 1\right)\frac{\aleph_1}{\beta S X_P^{\rho}} \tag{B.29}$$

$$\frac{\partial M_{F2}}{\partial L^*}\left(\frac{1}{M_{F2}}\right) = \frac{\rho - 1}{L + \alpha\beta S - \beta NW} \tag{B.30}$$

$$\frac{\partial M_1}{\partial NW^*}\left(\frac{1}{M_1}\right) = \left(\frac{\psi}{\eta} - 1\right)\frac{\delta\eta(PAX_P^{\gamma} + R_H(\bar{T} - S - L - HL) + V - \tau R_Z Z - B)^{\eta-1}\left[-PA\frac{\gamma}{\rho}X_P^{\gamma-\rho}\frac{\aleph_1}{S}\right] + \phi(1-\delta)\eta X_U^{\eta-1}}{\delta(PAX_P^{\gamma} + R_H(\bar{T} - S - L - HL) + V - \tau R_Z Z - B)^{\eta} + (1-\delta)X_U^{\eta}} \tag{B.31}$$

$$\frac{\partial M_2}{\partial NW^*}\left(\frac{1}{M_2}\right) = (\eta - 1)\frac{-PA\frac{\gamma}{\rho}X_P^{\gamma-\rho}\frac{\aleph_1}{S}}{PAX_P^{\gamma} + R_H(\bar{T} - S - L - HL) + V - \tau R_Z Z - B} \tag{B.32}$$

$$\frac{\partial M_3}{\partial NW^*}\left(\frac{1}{M_3}\right) = \left(\frac{\gamma}{\rho} - 1\right)\frac{-\aleph_1}{SX_P^{\rho}} \tag{B.33}$$

$$\frac{\partial M_{F2}}{\partial NW^*}\left(\frac{1}{M_{F2}}\right) = \frac{-\beta(\rho - 1)}{L + \alpha\beta S - \beta NW} \tag{B.34}$$

$$\frac{\partial M_4}{\partial NW^*} = \phi(1-\delta)\eta(\eta - 1)X_U^{\eta-2} > 0 \tag{B.35}$$

$$\frac{\partial M_1}{\partial HL^*} = \left(\frac{\psi}{\eta}\right)\left(\frac{\psi}{\eta} - 1\right)\frac{-R_H\delta\eta(PAX_P^{\gamma} + R_H(\bar{T} - S - L - HL) + V - \tau R_Z Z - B)^{\eta-1} + (1-\delta)\eta X_U^{\eta-1}}{\left[\delta(PAX_P^{\gamma} + R_H(\bar{T} - S - L - HL) + V - \tau R_Z Z - B)^{\eta} + (1-\delta)X_U^{\eta}\right]^{2-\frac{\psi}{\eta}}} \tag{B.36}$$

$$\frac{\partial M_4}{\partial HL^*} = (1-\delta)\eta(\eta - 1)X_U^{\eta-2} \tag{B.37}$$

$$\frac{\partial M_2}{\partial HL^*} = -R_H\delta\eta(\eta - 1)(PAX_P^{\gamma} + R_H(\bar{T} - S - L - HL) + V - \tau R_Z Z - B)^{\eta-2} \tag{B.38}$$

For estimation purposes, we assume the following:

- $NW \approx 0 \rightarrow$ Simplifies the production technology but is consistent with stylized fact of production at this time.
- $V \approx B \rightarrow$ Simplifies household income constraint.
- $\psi = 1 \rightarrow$ Utility function is CRS.
- $R_H \rightarrow$ Total off-farm income from the farm operator and spouse divided by the sum of off-farm work hours.
- $R_Z Z \rightarrow$ Total enterprise expenditures on seeds, fuel, fertilizer, and pesticides).
- $\alpha > 0 \rightarrow$ Partial automation gives $\tau R_Z Z = (1 - c) \cdot R_Z Z$, where c is varied in robustness checks.

The comparative statics can be simplified by recognizing that: (1) in equations (B.2)-(B.3), the $M_1 \cdot M_2$ terms drop, and (2) M_1 can be dropped in equations (B.4)-(B.5). However, given that our aim is to calculate elasticities with respect to α, these terms are needed. This is because dropping M_1 and M_2 is equivalent to rescaling the FONCs, which preserves the sign of the associated elasticities but not their magnitudes. As the denominator in the elasticity is measured in percent changes, the true level of $(dS^*/d\alpha)$ is needed, not a normalized or scaled version.

B.1 Signing the Comparative Statics

We have the following parameter estimates and expectations:

- $\psi = 1 \rightarrow$ homogeneity parameter of the utility function (we assume $\psi = 1$)
- $\eta < 1 \rightarrow$ substitution parameter for utility function; likely negative
- $\rho < 1 \rightarrow$ substitution parameter for production function; likely positive
- $\gamma \rightarrow$ homogeneity parameter of the production function; likely positive
- $\delta \in (0,1) \rightarrow$ utility share parameter; assume household gets utility from both (C) and $H_{tot}^{leisure}$
- $\alpha \in (0,1) \rightarrow$ degree of automation; assume partial automation
- $\beta \in (0,1) \rightarrow$ multi-tasked work time scale parameter
- $\phi \in (0,1) \rightarrow$ multi-tasked leisure time scale parameter
- $\tau \in (0,1] \rightarrow$ variable input expense reduction due to automation; assume non-zero
- $0 \leq \theta_j \leq 1$ for $j \in \{1, \ldots, 4\} \rightarrow$ input shares in production function

Based on these assumptions and on $C \equiv \left[PAX_P^{\gamma} - \tau R_Z Z + R_H(\bar{T} - S - L - HL) + V - B\right]$, we provide the anticipated sign (or ambiguity) for the comparative static components:

$$M_1 = \frac{\psi}{\eta}\left[\delta C^{\eta} + (1-\delta)X_U^{\eta}\right]^{\frac{\psi}{\eta}-1} = (-)\cdot(+) < 0 \tag{B.39}$$

$$M_2 = \delta\eta C^{\eta-1} = (-)\cdot(+) < 0 \tag{B.40}$$

$$M_3 = PA\left(\frac{\gamma}{\rho}\right)X_P^{\gamma-\rho} > 0 \tag{B.41}$$

$$M_4 = (1-\delta)\eta X_U^{\eta-1} < 0 \tag{B.42}$$

$$M_{F1} = \theta_1\rho S^{\rho-1} + \theta_2\rho(L + \alpha\beta S - \beta NW)^{\rho-1}\alpha\beta > 0 \tag{B.43}$$

$$M_{F2} = \theta_2\rho(L + \alpha\beta S - \beta NW)^{\rho-1} > 0 \tag{B.44}$$

$$\aleph_1 \equiv \theta_2\rho(L + \alpha\beta S - \beta NW)^{\rho-1}\cdot\beta S > 0 \tag{B.45}$$

$$\aleph_2 \equiv \theta_2\rho(L + \alpha\beta S - \beta NW)^{\rho-1}\cdot\alpha\beta + \theta_1\rho S^{\rho-1} > 0 \tag{B.46}$$

$$\frac{\partial M_1}{\partial\alpha}\left(\frac{1}{M_1}\right) = \left(\frac{\psi}{\eta}-1\right)\frac{\delta\eta C^{\eta-1}\cdot PA\frac{\gamma}{\rho}X_P^{\gamma-\rho}\cdot\aleph_1}{\delta C^{\eta} + (1-\delta)X_U^{\eta}} = (-)\frac{(-)}{(+)} > 0 \tag{B.47}$$

$$\frac{\partial M_2}{\partial\alpha}\left(\frac{1}{M_2}\right) = (\eta-1)\frac{PA\frac{\gamma}{\rho}X_P^{\gamma-\rho}\cdot\aleph_1}{C} = (-)\frac{(+)}{(+)} < 0 \tag{B.48}$$

$$\frac{\partial M_3}{\partial\alpha}\left(\frac{1}{M_3}\right) = \left(\frac{\gamma}{\rho}-1\right)\frac{\aleph_1}{X_P^{\rho}} = (+)\frac{(+)}{(+)} > 0 \text{ if } \gamma > \rho \tag{B.49}$$

$$\frac{\partial M_{F1}}{\partial\alpha}\left(\frac{1}{M_{F1}}\right) = \frac{\aleph_1}{\aleph_2}\left[\frac{1}{S} + \frac{\alpha\beta(\rho-1)}{(L + \alpha\beta S - \beta NW)}\right] = (+)\cdot\left[(+) + \frac{(-)}{(+)}\right] \rightarrow \ ? \tag{B.50}$$

$$\frac{\partial M_{F2}}{\partial\alpha}\left(\frac{1}{M_{F2}}\right) = (\rho-1)\frac{\beta S}{L + \alpha\beta S - \beta NW} = (-)\cdot(+) < 0 \tag{B.51}$$

$$\frac{\partial M_1}{\partial S^*}\left(\frac{1}{M_1}\right) = \left(\frac{\psi}{\eta}-1\right)\frac{\delta\eta(C)^{\eta-1}\left[PA\frac{\gamma}{\rho}X_P^{\gamma-\rho}\aleph_2 - R_H\right]}{\delta C^{\eta} + (1-\delta)X_U^{\eta}} = (-)\frac{[(-)(+?)]}{(+)} > 0 \text{ if last term in num} > 0 \tag{B.52}$$

$$\frac{\partial M_2}{\partial S^*}\left(\frac{1}{M_2}\right) = (\eta-1)\frac{PA\frac{\gamma}{\rho}X_P^{\gamma-\rho}\aleph_2 - R_H}{C} = (-)\frac{(+?)}{(+)} < 0 \text{ (likely)} \tag{B.53}$$

$$\frac{\partial M_3}{\partial S^*}\left(\frac{1}{M_3}\right) = \left(\frac{\gamma}{\rho}-1\right)\frac{\aleph_2}{X_P^{\rho}} = (+)\frac{(+)}{(+)} > 0 \text{ if } \gamma > \rho \tag{B.54}$$

$$\frac{\partial M_{F1}}{\partial S^*}\left(\frac{1}{M_{F1}}\right) = \frac{\rho-1}{\aleph_2}\left(\theta_1\rho S^{\rho-2} + \frac{\aleph_1\alpha^2\beta}{(L+\alpha\beta S-\beta NW)S}\right) = (-)\cdot(+) < 0 \tag{B.55}$$

$$\frac{\partial M_1}{\partial L^*}\left(\frac{1}{M_1}\right) = \left(\frac{\psi}{\eta}-1\right)\frac{\delta\eta C^{\eta-1}\left(PA\frac{\gamma}{\rho}X_P^{\gamma-\rho}\frac{\aleph_1}{\beta S} - R_H\right)}{\delta C^{\eta}+(1-\delta)X_U^{\eta}} = (-)\frac{[(-)(+?)]}{(+)} > 0 \text{ (likely)} \tag{B.56}$$

$$\frac{\partial M_2}{\partial L^*}\left(\frac{1}{M_2}\right) = (\eta-1)\frac{PA\frac{\gamma}{\rho}X_P^{\gamma-\rho}\frac{\aleph_1}{\beta S} - R_H}{C} = (-)\frac{(+?)}{(+)} < 0 \text{ (likely)} \tag{B.57}$$

$$\frac{\partial M_3}{\partial L^*}\left(\frac{1}{M_3}\right) = \left(\frac{\gamma}{\rho}-1\right)\frac{\aleph_1}{\beta S X_P^{\rho}} = (+)\frac{(+)}{(+)} > 0 \text{ if } \gamma > \rho \tag{B.58}$$

$$\frac{\partial M_{F2}}{\partial L^*}\left(\frac{1}{M_{F2}}\right) = \frac{\rho-1}{L+\alpha\beta S-\beta NW} = \frac{(-)}{(+)} < 0 \tag{B.59}$$

$$\frac{\partial M_1}{\partial NW^*}\left(\frac{1}{M_1}\right) = \left(\frac{\psi}{\eta}-1\right)\frac{\delta\eta C^{\eta-1}\left[-PA\frac{\gamma}{\rho}X_P^{\gamma-\rho}\frac{\aleph_1}{S}\right] + \phi(1-\delta)\eta X_U^{\eta-1}}{\delta C^{\eta}+(1-\delta)X_U^{\eta}} = (-)\frac{[(-)(-)+(-)]}{(+)} \to ? \tag{B.60}$$

$$\frac{\partial M_2}{\partial NW^*}\left(\frac{1}{M_2}\right) = (\eta-1)\frac{-PA\frac{\gamma}{\rho}X_P^{\gamma-\rho}\frac{\aleph_1}{S}}{C} = (-)\cdot\frac{(-)}{(+)} > 0 \tag{B.61}$$

$$\frac{\partial M_3}{\partial NW^*}\left(\frac{1}{M_3}\right) = \left(\frac{\gamma}{\rho}-1\right)\frac{-\aleph_1}{SX_P^{\rho}} = (+)\frac{(-)}{(+)} < 0 \text{ if } \gamma > \rho \tag{B.62}$$

$$\frac{\partial M_{F2}}{\partial NW^*}\left(\frac{1}{M_{F2}}\right) = \frac{-\beta(\rho-1)}{L+\alpha\beta S-\beta NW} = \frac{(+)}{(+)} > 0 \tag{B.63}$$

$$\frac{\partial M_4}{\partial NW^*} = \phi(1-\delta)\eta(\eta-1)X_U^{\eta-2} > 0 \tag{B.64}$$

$$\frac{\partial M_1}{\partial HL^*} = \left(\frac{\psi}{\eta}\right)\left(\frac{\psi}{\eta}-1\right)\frac{-R_H\delta\eta C^{\eta-1}+(1-\delta)\eta X_U^{\eta-1}}{\left[\delta C^{\eta}+(1-\delta)X_U^{\eta}\right]^{2-\frac{\psi}{\eta}}} = (-)\cdot(-)\frac{[(+)+(-)]}{(+)} \to \text{likely} < 0 \tag{B.65}$$

$$\frac{\partial M_4}{\partial HL^*} = (1-\delta)\eta(\eta-1)X_U^{\eta-2} > 0 \tag{B.66}$$

$$\frac{\partial M_2}{\partial HL^*} = -R_H\delta\eta(\eta-1)C^{\eta-2} < 0 \tag{B.67}$$

Further, we can sign additional terms underlying these components:

$$M_1 = \frac{\psi}{\eta}\left[\delta C^{\eta}+(1-\delta)X_U^{\eta}\right]^{\frac{\psi}{\eta}-1} < 0 \tag{B.68}$$

$$M_2 = \delta\eta C^{\eta-1} < 0 \tag{B.69}$$

$$M_3 = PA\left(\frac{\gamma}{\rho}\right)X_P^{\gamma-\rho} > 0 \tag{B.70}$$

$$M_4 = (1-\delta)\eta X_U^{\eta-1} < 0 \tag{B.71}$$

$$M_{F1} = \theta_1\rho S^{\rho-1} + \theta_2\rho(L+\alpha\beta S-\beta NW)^{\rho-1}\alpha\beta > 0 \tag{B.72}$$

$$M_{F2} = \theta_2\rho(L+\alpha\beta S-\beta NW)^{\rho-1} > 0 \tag{B.73}$$

$$\aleph_1 \equiv \theta_2\rho(L+\alpha\beta S-\beta NW)^{\rho-1}\cdot\beta S > 0 \tag{B.74}$$

$$\aleph_2 \equiv \theta_2\rho(L+\alpha\beta S-\beta NW)^{\rho-1}\cdot\alpha\beta + \theta_1\rho S^{\rho-1} > 0 \tag{B.75}$$

Also, we have: $\frac{\partial M_1}{\partial \alpha} < 0$, $\frac{\partial M_2}{\partial \alpha} > 0$, $\frac{\partial M_2}{\partial S^*} > 0$ (likely), $\frac{\partial M_1}{\partial S^*} < 0$ (likely), $\frac{\partial M_2}{\partial L^*} > 0$ (likely), $\frac{\partial M_1}{\partial L^*} < 0$ (likely), and $\frac{\partial M_1}{\partial NW^*} =$?.

B.1.1 Signing the Components

Given the signs of the sub-components above, we attempt to sign the detailed versions of the comparative statics (with respect to α) from each FONC:

$$\frac{dS^*}{d\alpha} = -\frac{\left[\frac{\partial M_1}{\partial \alpha}\left(\frac{1}{M_1}\right) + \frac{\partial M_2}{\partial \alpha}\left(\frac{1}{M_2}\right) + \frac{\partial M_3}{\partial \alpha}\left(\frac{1}{M_3}\right) + \frac{\partial M_{F1}}{\partial \alpha}\left(\frac{1}{M_{F1}}\right)\right] - R_H \frac{\partial M_2}{\partial \alpha} \cdot \left(\frac{1}{M_2 M_3 M_{F1}}\right) - R_H \frac{\partial M_1}{\partial \alpha} \cdot \left(\frac{1}{M_1 M_3 M_{F1}}\right)}{\left[\frac{\partial M_1}{\partial S^*}\left(\frac{1}{M_1}\right) + \frac{\partial M_2}{\partial S^*}\left(\frac{1}{M_2}\right) + \frac{\partial M_3}{\partial S^*}\left(\frac{1}{M_3}\right) + \frac{\partial M_{F1}}{\partial S^*}\left(\frac{1}{M_{F1}}\right)\right] - R_H \frac{\partial M_2}{\partial S^*} \cdot \left(\frac{1}{M_2 M_3 M_{F1}}\right) - R_H \frac{\partial M_1}{\partial S^*} \cdot \left(\frac{1}{M_1 M_3 M_{F1}}\right)}$$

$$= -\frac{[(+)+(-)+(+)+(?)] - R_H \cdot (+) \cdot \left(\frac{1}{(-)\cdot(+)\cdot(+)}\right) - R_H \cdot (-) \cdot \left(\frac{1}{(-)\cdot(+)\cdot(+)}\right)}{[(+)+(-)+(+)+(-)] - R_H \cdot (+) \cdot \left(\frac{1}{(-)\cdot(+)\cdot(+)}\right) - R_H \cdot (-) \cdot \left(\frac{1}{(-)\cdot(+)\cdot(+)}\right)} \tag{B.76}$$

$$\frac{dL^*}{d\alpha} = -\frac{\left[\frac{\partial M_1}{\partial \alpha}\left(\frac{1}{M_1}\right) + \frac{\partial M_2}{\partial \alpha}\left(\frac{1}{M_2}\right) + \frac{\partial M_3}{\partial \alpha}\left(\frac{1}{M_3}\right) + \frac{\partial M_{F2}}{\partial \alpha}\left(\frac{1}{M_{F2}}\right)\right] - R_H \frac{\partial M_2}{\partial \alpha} \cdot \left(\frac{1}{M_2 M_3 M_{F2}}\right) - R_H \frac{\partial M_1}{\partial \alpha} \cdot \left(\frac{1}{M_1 M_3 M_{F2}}\right)}{\left[\frac{\partial M_1}{\partial L^*}\left(\frac{1}{M_1}\right) + \frac{\partial M_2}{\partial L^*}\left(\frac{1}{M_2}\right) + \frac{\partial M_3}{\partial L^*}\left(\frac{1}{M_3}\right) + \frac{\partial M_{F2}}{\partial L^*}\left(\frac{1}{M_{F2}}\right)\right] - R_H \frac{\partial M_2}{\partial L^*} \cdot \left(\frac{1}{M_2 M_3 M_{F2}}\right) - R_H \frac{\partial M_1}{\partial L^*} \cdot \left(\frac{1}{M_1 M_3 M_{F2}}\right)}$$

$$= -\frac{[(+)+(-)+(+)+(-)] - R_H \cdot (+) \cdot \left(\frac{1}{(-)\cdot(+)\cdot(+)}\right) - R_H \cdot (-) \cdot \left(\frac{1}{(-)\cdot(+)\cdot(+)}\right)}{[(+)+(-)+(+)+(-)] - R_H \cdot (+) \cdot \left(\frac{1}{(-)\cdot(+)\cdot(+)}\right) - R_H \cdot (-) \cdot \left(\frac{1}{(-)\cdot(+)\cdot(+)}\right)} \tag{B.77}$$

$$\frac{dNW^*}{d\alpha} = -\frac{\left[\frac{\partial M_1}{\partial \alpha}(\frac{1}{M_1}) + \frac{\partial M_2}{\partial \alpha}(\frac{1}{M_2}) + \frac{\partial M_3}{\partial \alpha}(\frac{1}{M_3}) + \frac{\partial M_{F2}}{\partial \alpha}(\frac{1}{M_{F2}})\right] + \phi\left(M_4 \frac{\partial M_1}{\partial \alpha}\right) \cdot \left(\frac{1}{-\beta M_1 M_2 M_3 M_{F2}}\right)}{\left[\frac{\partial M_1}{\partial NW^*}(\frac{1}{M_1}) + \frac{\partial M_2}{\partial NW^*}(\frac{1}{M_2}) + \frac{\partial M_3}{\partial NW^*}(\frac{1}{M_3}) + \frac{\partial M_{F2}}{\partial NW^*}(\frac{1}{M_{F2}})\right] + \phi\left(M_1 \cdot \frac{\partial M_4}{\partial NW^*} + M_4 \frac{\partial M_1}{\partial NW^*}\right) \cdot \left(\frac{1}{-\beta M_1 M_2 M_3 M_{F2}}\right)}$$

$$= -\frac{[(+)+(-)+(+)+(-)] + \phi\,[(-)\cdot(-)] \cdot \left(\frac{1}{-\beta\cdot(-)\cdot(-)\cdot(+)\cdot(+)}\right)}{[(?)+(+)+(-)+(+)] + \phi\,((-)\cdot(+)+(-)\cdot(?)) \cdot \left(\frac{1}{-\beta\cdot(-)\cdot(-)\cdot(+)\cdot(+)}\right)} \tag{B.78}$$

$$\frac{dHL^*}{d\alpha} = -\frac{-R_H \cdot M_1 \cdot \frac{\partial M_2}{\partial \alpha} + \frac{\partial M_1}{\partial \alpha}(M_4 - R_H \cdot M_2)}{M_1\left(\frac{\partial M_4}{\partial HL^*} - R_H \frac{\partial M_2}{\partial HL^*}\right) + \frac{\partial M_1}{\partial HL^*}(M_4 - R_H \cdot M_2)} \tag{B.79}$$

$$= -\frac{-R_H \cdot (-) \cdot (+) + (-) \cdot [(-) - R_H \cdot (-)]}{(-) \cdot [(+) - R_H \cdot (-)] + (-) \cdot [(-) - R_H \cdot (-)]}$$

Ultimately, we see that each of the comparative statics terms are ambiguous in sign. However, given the intuition suggested in the main text above, it seems likely that $\frac{dS^*}{d\alpha} < 0$, $\frac{dL^*}{d\alpha} < 0$, and $\frac{dHL^*}{d\alpha} > 0$.

B.2 Note on Equivalence of First-Order Conditions in Appendices A and B

To illustrate this equivalence, consider the FONC with respect to W from Appendix A:

$$\frac{\partial \mathcal{L}}{\partial W} = M_1 \cdot M_2 \cdot M_3 \cdot \theta_2 \cdot \rho(L + \beta W)^{\rho-1} \cdot \beta - \lambda_2 = 0. \tag{A.9}$$

Substitute $W = \alpha S - NW$, so that $L + \beta W = L + \beta(\alpha S - NW)$. The chain rule[25] gives:

$$\frac{\partial \mathcal{L}}{\partial NW} = -\frac{\partial \mathcal{L}}{\partial W}.$$

Thus,

$$\frac{\partial \mathcal{L}}{\partial NW} = -M_1 \cdot M_2 \cdot M_3 \cdot \theta_2 \cdot \rho(L + \beta(\alpha S - NW))^{\rho-1} \cdot \beta + \frac{\partial \mathcal{L}}{\partial NW}\Big|_{\text{leisure term}}.$$

The derivative of the utility term with respect to NW is:

$$\frac{\partial \mathcal{L}}{\partial NW}\Big|_{\text{leisure term}} = M_1 \cdot M_4 \cdot \phi.$$

Putting both parts together:

$$\frac{\partial \mathcal{L}}{\partial NW} = -M_1 \cdot M_2 \cdot M_3 \cdot MF_2 \cdot \beta + M_1 \cdot M_4 \cdot \phi = 0, \tag{B.8}$$

where $MF_2 = \theta_2 \cdot \rho \cdot (L + \beta(\alpha S - NW))^{\rho-1}$. This confirms the equivalence between the transformed version of (A.9) and the direct FONC in (B.8).

[25] Since $W = \alpha S - NW$, differentiating both sides with respect to NW gives $\frac{dW}{dNW} = -1$. By the chain rule, this implies $\frac{\partial \mathcal{L}}{\partial NW} = \frac{\partial \mathcal{L}}{\partial W} \cdot \frac{dW}{dNW} = -\frac{\partial \mathcal{L}}{\partial W}$.

C Estimation of Alpha

Regression Approach

To estimate α, we begin by assuming that non-work multitasking time (NW) is negligible, so that $\alpha \approx \frac{W}{S}$. This assumption is plausible for our 2001-2004 sample, when automated guidance technologies were less sophisticated (e.g., Light Bar in early years) and in-cab mobile entertainment options (e.g., streaming video, podcasts) were not available.

Rearranging yields $W = \alpha S$. Accordingly, a simple regression of cab-based work time (W) on total steering time (S), which is our proxy for potential multitasking time, would identify α. Based on this, a simple regression of time spent on non-automated work tasks in the cab (W) on total steering time (i.e., potential multitasking time) would yield an estimate of α. We adopt this specification as a baseline but introduce several modifications to reflect data availability and context.

First, we derive S_i from 2001–2004 ARMS Phase 2 data. Because steering time only translates into multitasking opportunities when automated guidance is present, we interact S_i with an indicator for guidance adoption, $G_i \in \{0, 1\}$, yielding the modified regression:

$$W_i = \mu S_i + \alpha(S_i \times G_i)$$

Second, we approximate W_i using time spent on cab-feasible work activities reported in the ARMS time use data. From the available time specific tasks, we approximate W_i using time spent on scouting, irrigation, and overhead.

We therefore estimate the following regression, where $Scouting$, $Irrigation$, and $Overhead$ are indicator variables if the farmer had time spent on each activity, $Acreage$ is a continuous measure of the commodity's enterprise acreage, and $\mathbf{X}_i$ is a set of fixed effects (crop, state, year, and state–year interactions) that differ across specifications:

$$W_i = \mu S_i + \alpha(S_i \times G_i) + \beta_1 \cdot Scouting_i + \beta_2 \cdot Irrigation_i + \beta_3 \cdot Overhead_i + \beta_4 Acreage_i + \boldsymbol{\beta_X X_i}$$

The coefficient of interest is the interaction term $(S_i \times G_i)$, which provides an approximation for α. Table C.1 provides summary statistics for the data used in the regression estimation, while Table C.2 reports results for two specifications that differ only in their fixed-effects structure. Both specifications produce $\hat{\alpha} \approx 0.30$–$0.31$, leading to our baseline value of $\alpha = 0.30$ in our analysis.[26]

Survey Approach

As a check on the plausibility of $\alpha = 0.30$, we introduced a precision agriculture module in the 2025 Iowa Farm and Rural Life Poll, a survey of Iowa farmers conducted annually since 1982 to provide timely and relevant information on agriculture and rural life in Iowa. The sample, consisting of roughly 1,000 farmers across the state, is designed to be representative of Iowa crop production, partly with the help of survey frames from USDA's National Agricultural Statistics Service (NASS). The survey is administered by Iowa State University through its Center for Survey Statistics and Methodology (Iowa State University, 2025).

As part of module, we asked survey respondents "If you use autosteer during planting, on average how do you divide up your time? If you do not use autosteer during planting, please provide your opinion of how you would divide up your time if you did." The question contained five response choices: (1) Focused on the fieldwork (e.g., monitoring steering, equipment, data, etc.), (2) Other farm-related tasks (e.g., work emails, market analysis, farm-related podcasts), (3) Non-farm work-tasks, (4) Non-work activities or relaxation (e.g., reading, podcasts, videos, emails/texts), and (5) Other. The average amount of time allocated to the task at hand was 65%, implying that respondents engaged in multi-tasking for 35% of their in-cab time. Histograms of the distributions of these time allocations, by autosteer adopter and nonadopter status, are shown in Figure C.1.

[26] Including a constant term leaves the point estimates virtually unchanged and is therefore omitted for brevity.

Table C.1: Summary Statistics for α Estimation

Variable	Mean/Proportion	Std. Error	95% CI Lower	95% CI Upper
Field Labor Hours	15.98	0.55	14.80	17.17
Steering	21.75	0.43	20.82	22.68
Steering × Guidance	1.53	0.12	1.27	1.80
Scouting	0.77	0.012	0.74	0.79
Irrigation	0.06	0.004	0.05	0.07
Overhead	0.75	0.009	0.73	0.77
Acreage	745	75	584	906
Year Distribution				
2001	0.175	0.009	0.157	0.195
2002	0.398	0.012	0.372	0.424
2003	0.163	0.005	0.153	0.173
2004	0.265	0.012	0.240	0.291
Crop Distribution				
Barley	0.032	0.002	0.028	0.038
Corn	0.175	0.009	0.157	0.195
Cotton	0.092	0.005	0.082	0.102
Durum Wheat	0.009	0.002	0.006	0.013
Peanuts	0.013	0.001	0.012	0.015
Sorghum	0.038	0.003	0.033	0.045
Soybeans	0.398	0.012	0.372	0.424
Spring Wheat	0.058	0.005	0.048	0.069
Winter Wheat	0.185	0.009	0.166	0.205
State Distribution				
AL	0.008	0.001	0.006	0.011
AZ	0.002	0.000	0.001	0.002
AR	0.029	0.011	0.012	0.066
CA	0.002	0.000	0.002	0.003
CO	0.015	0.002	0.011	0.021
FL	0.001	0.000	0.001	0.002
GA	0.017	0.002	0.014	0.021
ID	0.010	0.001	0.008	0.011
IL	0.087	0.006	0.075	0.102
IN	0.051	0.006	0.039	0.066
IA	0.065	0.008	0.050	0.085
KS	0.073	0.005	0.062	0.085
KY	0.011	0.002	0.008	0.015
LA	0.004	0.000	0.004	0.005
MD	0.005	0.002	0.003	0.010
MI	0.030	0.003	0.025	0.035
MN	0.050	0.004	0.042	0.060
MS	0.016	0.004	0.010	0.028
MO	0.044	0.004	0.037	0.052
MT	0.034	0.005	0.025	0.045
NE	0.048	0.004	0.040	0.058
NY	0.008	0.004	0.003	0.020
NC	0.062	0.008	0.047	0.081
ND	0.047	0.003	0.041	0.055
OH	0.048	0.004	0.040	0.056
OK	0.030	0.003	0.023	0.037
OR	0.003	0.000	0.002	0.003
PA	0.013	0.002	0.010	0.018
SC	0.004	0.000	0.003	0.005
SD	0.034	0.002	0.029	0.039
TN	0.013	0.002	0.010	0.017
TX	0.081	0.008	0.066	0.099
UT	0.001	0.000	0.001	0.002
VA	0.008	0.001	0.006	0.011
WA	0.006	0.001	0.005	0.007
WI	0.041	0.005	0.032	0.053
WY	0.001	0.000	0.001	0.001

Notes: Field labor hours are the sum of time spent scouting for weeds and insects, irrigating, and for overhead activities. Standard errors are estimated using the delete-a-group jackknife procedure, using replicate weights provided by USDA-NASS.

Table C.2: Regression Results for α Estimation

	(1)	(2)
Steering	0.239***	0.224***
	(0.026)	(0.030)
Steering × Guidance	0.314**	0.303*
	(0.146)	(0.152)
Scouting	3.814*	4.371**
	(1.920)	(1.934)
Irrigation	46.251***	42.599***
	(3.914)	(3.988)
Overhead	13.698***	13.571***
	(1.461)	(1.447)
Acreage	−0.001	−0.001
	(0.001)	(0.001)
Year FE	Yes	Yes
State FE	Yes	Yes
Year × State FE	No	Yes
Crop FE	Yes	Yes
N (obs)	9,101	

Notes: Estimates from survey-weighted linear regressions. Standard errors in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Models (1) and (3) differ by inclusion of year × state fixed effects.



Figure C.1: Autosteer Time Use, 2025 Iowa Farm and Rural Life Poll

D Calibration of Beta

In the optimization problem provided in (7), β represents the marginal rate of technical substitution (MRTS) between multi-tasked and dedicated work time. We use data from the United Kingdom's Time Use Survey (UKTUS) (ONS, 2019) and Autor and Dorn (2013) to approximate how U.S. farmers might trade off multi-task work time in the cab relative to dedicated work time outside the cab.

In the 2014-15 wave of the UKTUS, 4,371 UK households—including a sample of farm households—were surveyed about their time use, collecting data about all activities in 10-minute intervals for two 24-hour periods. We implement a multi-step mapping procedure to link the UKTUS data with Autor and Dorn (2013)'s U.S. data. The Autor and Dorn (2013) data, henceforth referred to as "AD", contain occupational codes (linked to the 2010 U.S. Census) along with a Routine Task Intensity (RTI) score and the underlying measures for routine, manual, and abstract tasks for each code. The AD to UKTUS mapping allows us to determine which households' jobs are close to fully automatable. The UKTUS diary entries also provide sufficient information to estimate each individual's total work hours and multi-tasking time (i.e., "other activities").[27]

Our calibration of β relies on the following premise: for people with fully automatable jobs, all of their work time is potential multi-task time. The degree to which they actually multi-task relative to the total opportunity to multi-task provides an approximation for β. That is, using individuals with fully or close to fully automatable jobs (i.e., higher RTI scores), we can calibrate β by calculating the actual multi-task time relative to their total work time.

We acknowledge important differences between U.K. and U.S. work patterns, as well as between agricultural and non-agricultural households. While the UKTUS is not U.S.-specific, it remains the only publicly available dataset with sufficient time-use detail (including multi-tasking) to support calibration of β. However, given potential concerns about transferability (i.e., external validity), we provide sensitivity analysis to our derived estimates of β.

D.1 Steps to calibrate beta

Calibration of β proceeded via the following steps:

1. Occupational codes and RTI scores from AD were linked with UK Standard Occupational Classification (SOC) 2010 codes; various measures related to the RTI score (e.g., terciles, quartiles, quintiles, and deciles) were calculated for each UK SOC 2010 code (see next subsection for details).
2. UKTUS data on individual time use and occupation were merged with the UK SOC 2010 occupation and RTI dataset.
3. The UKTUS 10-minute diary entries were used to calculate total work time and multi-tasking time for each individual; β was calculated for each individual based on the multi-task time relative to total work time.
4. Individual β estimates and corresponding occupational codes were used to derive a β estimate for each occupation code.
5. An overall estimate of β was calculated by averaging across occupations with high automation potential as measured by the RTI scores; sensitivity of the overall estimate of β was tested using different RTI thresholds (e.g., third tercile, fourth quartile).

D.2 Linking Autor and Dorn (2013) data with UK SOC 2010 codes

To complete step 1 from the above calibration procedure, we implemented a multi-step mapping procedure to link the AD (U.S. Census 2010) occupation codes and corresponding RTI scores to the UK SOC 2010 classification. First, the AD occupational codes were mapped to U.S. Standard Occupational Classification (SOC) 2010 codes. These were subsequently aligned with International Standard Classification of Occupations (ISCO-08) codes, and finally with UK SOC 2010 codes. The resulting chained crosswalk was used to construct a preliminary match file that linked AD occupational codes, along with their corresponding RTI scores, with UK SOC 2010 codes. All preliminary one-to-one matches were manually reviewed for accuracy and adjusted as appropriate.

Cases involving multiple AD codes mapped to a single UK SOC code were manually reviewed and resolved as appropriate. RTI values were calculated as the average of the three closest-matched AD codes. Similarly, unmatched

[27] While self-reported work time data have known limitations, including potential recall bias and misreporting (Borjas and Hamermesh, 2024), we use diary entry data here solely to approximate α at the aggregate level. Our objective is not to analyze individual-specific time allocation but to calibrate a parameter relevant to our broader modeling context, for which diary-based averages are sufficiently informative.

UK SOC codes were reviewed and manually mapped to up to three AD codes, with the resulting RTI value reflecting the average RTI score across the mapped AD codes.[28]

Table D.1: Tasks and Activitites to Link Autor and Dorn (2013) with UK SoC 2010

Task	**Description of Activities**
Mapping Across Classification Systems	Mapped AD codes to UK SOC 2010 using intermediate mappings: US Census 2010 → US SOC 2010 → ISCO-08 → UK SOC 2010 Crosswalk scripts resulted in three data sets: one-to-one matches, many-to-one matches, and unmatched UK SOC codes.
One-to-One Match Verification	Verified one-to-one matches for accuracy.
Manual Review of Many-to-One Matches	Manually reviewed UK SOC codes that matched to multiple AD codes for accuracy. Derived average RTI score using up to three closest matched AD codes.
Manual Review of Unmatched Codes	Unmatched codes were examined manually and matched with up to three AD codes. Derived average RTI score using up to three closest matched AD codes.
Final Merge	Generated final file containing all UK SOC codes and corresponding RTI scores derived from the one-to-one, many-to-one, and unmatched processes above.

[28] Manual matching was aided by the UK's Occupational Coding Tool (no longer active), which returned suggested UK SOC codes for user-provided job titles and tasks.

E Data Overview

We provide an overview of the key variables in the information below. Table E.1 contains more detail about each of the variables and their sources.

Variables Construction

- **Steering time (S)** and **guidance (G)**: Recall that S is the principal operator's hours spent on steering crop production equipment that could have benefited from autosteer during 2001-04. ARMS Phase II records the hours the operator spent on all machine operations (e.g. tillage, planting, harvesting) for the target crop in the randomly surveyed field, which we scale up to the enterprise. Hours spent (1) driving cars or trucks, (2) using land-forming or hauling machinery, (3) using aerial equipment (e.g., chemical applications via airplane), (4) performing horse-drawn operations, and (5) using other non-relevant equipment are removed prior to construction. Because steering time translates into multitasking opportunities only when autosteer is used, we also define an indicator G for autosteer guidance adoption. Autosteer adoption is observed in the ARMS Phase II data as a yes/no response for whether guidance technology was used on the field to produce the target crop.

- **Manual (non-automated) labor (L)**: This measures the principal operator's manual farm labor hours devoted to the commodity during the season. We obtain this information from Phase III farm survey data on how many average hours the operator spent on farm labor each week, by quarter of year. For each operator, we multiply weekly hours by the number of weeks in each quarter, sum across quarters, and then scale by the number of months in the commodity's season.

- **Work time (W)** and **leisure time (NW) from automation**: Since W is not directly observed in ARMS, we construct the variable from a combination of field-level time spent on scouting, irrigation, and overhead/management tasks. We use these task hours to approximate W, under the assumption that with autosteer, the operator can work on these (or related) tasks concurrently while the machine self-steers. Recall that our estimation strategy does not directly rely on use of NW, though for the purposes of calculating the elasticity of W with respect to α, we set $NW = 0.05S$.

- **Off-farm work hours (H_{off})**: Although H_{off} is not used directly in the estimating equation, this variable is needed in our construction of HL below. ARMS Phase III inquires about (1) how many weeks the operator worked for pay off-farm in the calendar year, and (2) during the weeks the operator worked for pay off-farm, how many average hours per week were worked. To derive H_{off}, we multiply each of these items and re-scale it to the season-enterprise level.

- **Dedicated leisure (HL)**: With the above variables in hand, we calculate HL by assuming the household's time constraint binds. To first construct $\bar{T}$, we multiply each observation-specific season length (in months) by the number of hours per month and then rescale to the enterprise level (assuming the season length for the field is broadly representative of the season length for the entire crop enterprise); thus, $HL = \bar{T} - S - L - H_{off}$. Because HL also includes sleep time, and because H_{off} is relatively low, HL tends to have large values.

- **Variable input (Z)**: We construct an index of variable inputs used, Z, to represent the aggregate quantity of intermediate inputs (seeds, fuel, fertilizer, and chemicals) applied in the

crop enterprise. We use total expenditures reported on these in ARMS Phase III and deflate by using NASS' Prices Paid Index for each of the four categories. The resulting variable is a unitless index, where higher values indicate greater input usage in real terms. Similarly, per-acre input expenditures ($\boldsymbol{R_z Z}$), which we use as controls in the first-stage regressions, are equal to these expenditure values divided by the enterprise acreage.

- **Capital ($\boldsymbol{K}$)**: The capital input is measured as the value of farm assets used in production. We use the total reported value of farm capital stock—including land (owned land value allocated to the enterprise acres), machinery (tractors, combines), structures, and other equipment—as a proxy for the productive capital available to the crop enterprise, which we scale to the enterprise level.

- **Crop output ($\boldsymbol{Q}$)**: Output is the total production of the crop enterprise, measured in physical units (pounds of harvested crop), which we obtain from ARMS Phase III. We pair Q with state-level data on $\boldsymbol{P}$ (dollars per pound), from NASS' Agricultural Prices program, to construct total enterprise revenue, where needed.

- **Total factor productivity ($\boldsymbol{A}$)**: The state-level TFP index (A), capturing exogenous productivity across states and time, comes from ERS' state-level productivity accounts. These data, based on a translog transformation frontier, are relative to a base of 1996 in Alabama.

- **Other variables**: Two other variables in the underlying economic model are worth noting. The off-farm wage rate, $\boldsymbol{R_H}$, is constructed by taking ERS' estimates of total farm household off-farm income (which involves some internal imputation) and dividing by the household's number of hours worked. To operationalize $\boldsymbol{\tau}$, the mark-down in variable input expenses equal to $(\mathbf{1} - \boldsymbol{c})$ for autosteer adopters, we first calculate reductions in expenses by category. We compute sample means for seed, fuel, fertilizer, and chemical expenditures, for both adopters and nonadopters. The decrease in each expense category is then constructed as the ratio of the mean expense for adopters to the mean expense for non-adopters. For simulation purposes, we can construct the total variable input expense associated with automation ($\boldsymbol{R_Z Z}$) as the sum of the products of each variable input expense with the

The remaining variables, including those used in the reduced-form first stage regressions and their empirical constructs, are described in more depth in the table below.

Table E.1: Variable Descriptions and Sources

Model Variable	**Description**	**Source**
Steering time (S)	Principal operator's steering hours during the season	USDA, ARMS Phase II data
Labor time (L)	Principal operator's labor hours during the season	USDA, ARMS Phase III data
Variable inputs (Z)	Index of seed, fuel, fertilizer, and seed used	USDA, ARMS Phase III data
Capital assets (K)	Value of assets used in farm production (structures, land, trucks, cars, tractors, and other equipment)	USDA, ARMS Phase III data
Crop output (Q)	Total enterprise crop production (lbs)	USDA, ARMS Phase III data
Total leisure time (HL)	Principal operator's leisure hours during the season	USDA, ARMS Phase III data
Consumption (C)	Total dollar amount spent on household and living expenses (including entertainment, investments, charitable contributions, pension deductions)	USDA, ARMS Phase III data
Auto-steer use (G)	Indicator variable if operator used autosteer on field to produce target crop	USDA, ARMS Phase II data
Total factor productivity (A)	State-level total factor productivity (TFP)	ERS, State productivity accounts
Output price (P)	State-average output price received, measured in $ per pound	NASS, Agricultural Prices program
Maximum horsepower (HP^{Max})	Max. horsepower of all tractors used on field to produce target crop	USDA, ARMS Phase II data
Minimum horsepower (HP^{Min})	Min. horsepower of all tractors used on field to produce target crop	USDA, ARMS Phase II data
Above median no. of passes	Indicator variable if field had above median number of passes for target crop	USDA, ARMS Phase II data
Principal operator is hired	Indicator variable if principal operator was a hired, non-owner operator	USDA, ARMS Phase III data
Contract labor used	Indicator variable if any contract labor was used on the field to produce target crop	USDA, ARMS Phase II data
Operator's age	Age of the principal operator	USDA, ARMS Phase III data
Any college	Indicator variable if principal operator has at least some college education	USDA, ARMS Phase III data
White operator	Indicator variable if principal operator's race is white	USDA, ARMS Phase III data
Grain-oilseeds-cotton-hay farm	Indicator variable if the largest portion of the farm's gross farm income came from production of grains, oilseeds, dry beans, dry peas, cotton/cottonseed, other non-specialty crops, or hay	USDA, ARMS Phase III data
Erodible land	Indicator if NRCS has ever classified the field as highly erodible	USDA, ARMS Phase II data
Total farm size	Total acres of farmland in the survey year	USDA, ARMS Phase III data
Commodity enterprise size (Ac)	Total acres planted to the target crop in the survey year	USDA, ARMS Phase III data
Custom service costs/ac	Per-acre costs of all custom services used on field to produce crop	USDA, ARMS Phase II data
Seed, fuel, fert, & chem expenditures/ac	Per-acre enterprise expenditures on seeds, fuel, fertilizers, and chemicals	USDA, ARMS Phase III data
Crop worker wage rate (WR)	State-level mean wage rate for agricultural equipment operators (45-2091)	BLS, OES data
Per capita personal income ($PCPI$)	County-level per capita personal income	BEA, CAINC30 data
Share farm proprietor jobs (SH)	County-level share of farm proprietor jobs	BEA, CAINC30 data
Unemployment rate (UR)	County-level unemployment rate	BLS, LAUS data

Notes: ARMS = Agricultural Resource Management Survey, ERS = Economic Research Service, NASS = National Agricultural Statistics Service, NRCS = Natural Resources Conservation Service, BLS = Bureau of Labor Statistics, OES = Occupational Employment and Wage Statistics (OEWS) program, BEA = Bureau of Economic Analysis, CAINC30 = County and Personal Income 30, LAUS = Local Area Unemployment Statistics. Unless otherwise noted, all variables have been scaled to the commodity enterprise during the season