DRAFT – For review only; results are preliminary and subject to revision

Predict and Attack (or Don't): An Econometric Approach to Large Wildfire Early Detection and Suppression Effectiveness

Hari Katuwal*
Tarleton State University, Stephenville, TX, 76401, USA
E-mail: katuwal@tarleton.edu

Michael S. Hand†
Rocky Mountain Research Station, USDA Forest Service, Missoula, MT, 59801, USA

Matthew Thompson†
Rocky Mountain Research Station, USDA Forest Service, Missoula, MT, 59801, USA

Crystal Stonesifer†
Rocky Mountain Research Station, USDA Forest Service, Missoula, MT, 59801, USA

David E. Calkin†
Rocky Mountain Research Station, USDA Forest Service, Missoula, MT, 59801, USA

Selected Paper prepared for presentation at the 2018 Agricultural & Applied Economics Association Annual Meeting, Washington, D.C., August 5-August 7

---

* Corresponding author. Tel.: +254968 9907. *E-mail address:* katuwal@tarleton.edu (Hari Katuwal)
† The views expressed here are those of the authors and do not necessarily represent the U.S. Department of Agriculture or USDA Forest Service.

Abstract:

Large air tankers (LATs) – fixed wing aircraft used for wildfire suppression – are an integral but costly tool for wildfire management. But little evidence is available indicating whether the deployment of LATs is effective at containing fire ignitions during initial attack. Using data on USDA Forest Service wildfire ignitions and LAT deployments from 2010-2012 this paper estimates the effect of deploying a LAT on the likelihood that the fire ignition is contained during initial attack. Results suggest that LATs may be effective for a subset of ignitions with moderate growth potential, but not for ignitions with very high or very low growth potential. However, identifying the treatment effect independent of other factors that determine both deployment and the likelihood of escape remains difficult, and it is possible that LATs are used to achieve objectives not captured by observation of initial attack success.

Keywords: Wildfire management, Large Air Tanker, Initial attack success

JEL Classification: Q23, D24, C36

Introduction

Large air tankers (LATs) are an integral component of wildfire suppression activities in the United States. The U.S. Forest Service, among the public agencies with the largest wildfire management responsibilities, spends an average of more than $100 million (2017 dollars) on LAT operations each year to support wildfire management.[3] Air tankers are often in high demand during times of high fire activity due to their ability to access new ignitions relatively quickly. However, LAT use, along with other aviation activities, is also a dangerous endeavor. Aviation for wildfire management has accounted for 59 fatalities due to accidents since from 2000 to 2012; of these 19 fatalities involved LATs (Stonesifer *et al.* 2014).

Despite their cost and risk, little is known about the operational effectiveness of wildfire aviation operations in general, and of LATs in particular, for containing new ignitions before they can grow large and become damaging wildfires. In general earlier arrival time of suppression resources is associated with increased likelihood of containing fires during initial attack (Arienti *et al.* 2006; Morin *et al.* 2015). Aircraft arrival times have been shown to be related to the likelihood that ignitions remain small and are contained quickly for a sample of fires igniting in forest and brush land in Australia (Plucinski *et al.* 2012), but not for a sample of grass fires (Plucinski 2013). A doubling of firefighting helicopter capacity in Tuscany, Italy was associated with a small but not statistically significant decrease in area burned (Marchi *et al.* 2014).

In this paper we attempt to estimate the effect of LAT deployment on the likelihood that a new fire ignition is contained during initial attack and does not develop into a large and potentially damaging wildfire. Using observations of fire ignitions on USDA Forest Service land, detailed

[3] Air tanker expenditures for Forest Service contracted aircraft are tracked through the aviation business system. Available at: https://www.fs.fed.us/business/abs/. Accessed May 23, 2018.

operational LAT data, and information about the growth potential of ignitions, we estimate the marginal effect of deploying a LAT on the likelihood that a new ignition will not escape containment efforts during initial attack.

Developing empirical evidence of the effectiveness of LATs may help wildfire managers make strategic and tactical decisions about when LAT deployment may be beneficial, and when it may not. Wildfire managers are able to express when they think that air tankers could be effective in initial attack scenarios (Plucinski *et al.* 2012). Expert assessments and operational understanding surely form an important component of the evidence base for suppression resource deployment decisions. But like many complex decision environments, wildfire management has been demonstrated to be subject to common decision biases (Wilson *et al.* 2011), risk aversion and probability weighting (Hand *et al.* 2015), and socio-political pressures that favor aggressive suppression responses (Donovan *et al.* 2011). Adding rigorous empirical evidence to expert judgements may help managers use suppression resources more effectively and efficiently to achieve desired fire management outcomes.

Background – What do we know about LAT use and effectiveness?

Air tankers, and aviation resources in general, are an important but costly component of Federal wildfire suppression efforts. Large air tankers – currently defined as fixed-wing aircraft with a tank load capacity of at least 3,000 gallons – are deployed to an average of about 2 percent of Forest Service fires each year. But expenditures on air tankers accounts for more than 7 percent of all suppression expenditures for the U.S. Forest Service (over the 8-year period 2010-2017)[4]. Air tankers are more commonly used on larger fires; more than half of fires greater than 40 hectares in size received air tankers (Calkin *et al.* 2014).

Operational guidance suggests that LATs are a tool primarily designed for initial attack operations (National Multi-Agency Coordinating Group 2018). Data on LAT use for US Forest Service fires suggests that LATs are indeed used primarily during initial attack, but that a substantial portion of LAT deployments are to fires that have escaped initial attack efforts; from 2010-2012 about 45 percent of air tanker use on Forest Service fires occurred after initial attack (Stonesifer *et al.* 2016). Observations of LAT use also suggests that fire containment remains a primary objective for LAT deployments; LAT use is concentrated near human populations where communities may be at risk from fire and near critical wildlife habitat where protection from wildfire is a priority (Stonesifer *et al.* 2016).

An endogenous treatment effects model of initial attack success

Simple model set up

The primary hypothesis of this study is that deploying a large air tanker to a wildfire ignition, and dropping chemical retardant at least once during initial attack, decreases the chance that the ignition will escape initial attack and grow to become a large wildfire. This hypothesis assumes that the objective of wildfire initial attack operations is to limit fire growth and to contain the

[4] Suppression expenditures for the Forest Service are summarized by the National Interagency Fire Center. Available at: https://www.nifc.gov/fireInfo/fireInfo_documents/SuppCosts.pdf. Accessed May 23, 2018. See footnote 3 for air tanker expenditures.

ignition as quickly as possible, and that air tankers are deployed for the purpose of extinguishing or containing fire. Other objectives are possible; instead of completely containing an ignition fire managers may seek to prevent fire spread along one portion of a fire (e.g., to protect homes or infrastructure in that direction) while allowing spread along a different portion (e.g., to allow burning in an area with little risk to lives and property). It is also possible that air tankers could be used not necessarily to contain a fire but to slow its spread to allow for evacuation operations.

In practice we know that the primary objective of initial attack is not always to limit fire growth or achieve quick containment. And, there is no suitable data or information available to consistently observe initial attack objectives for each ignition. However, the assumption that the initial attack objective is containment or limited fire growth may still be valid. Casual observation suggests that public firefighting agencies still place value on achieving a high initial attack success rate; budget justifications for the Forest Service and Department of the Interior highlight the high initial attack success rates as justification for maintaining wildfire preparedness funding (US Department Of The Interior 2018; USDA Forest Service 2018). For example, the Forest Service reported a 97% initial attack success rate (fires suppressed below 300 acres, or 121 hectares) in fiscal year 2017 (USDA Forest Service 2018). And during times when fire danger is acute managers may prefer containment as a strategy to actively choosing to let some ignitions grow large.

A difficulty in examining the effectiveness of LAT (or other suppression resources) is that we cannot observe fire outcomes that would have resulted had an LAT not been deployed on an ignition that in fact received and LAT, or if an LAT had been deployed on an ignition that did not receive an LAT. If deployment of LATs conditional on observables were independent of likelihood of escape, we could estimate a limited dependent variable model of initial attack outcomes (escape or not) by observing whether an LAT was deployed and covariate measures to yield an unbiased estimate of the LAT treatment effect. A latent-index model of the dependent variable provides a flexible formulation for empirical analysis:

$$(1)\ Y_i^* = \alpha + \beta T_i + X_i'\gamma + \mu_i,$$
$$(2)\ Y_i = \begin{cases} 1\ if\ Y_i^* > 0 \\ 0\ if\ Y_i^* \leq 0 \end{cases}.$$

where Y_i^* is an unobserved dependent variable index of the likelihood of initial attack success for fire ignition i, we observe initial attack outcomes for each ignition as Y_i (where $Y_i = 1$ indicates containment and $Y_i = 0$ indicates escape), T_i indicates whether the ignition received a LAT deployment during initial attack, X_i is a vector of exogenous explanatory variables, and μ_i is a zero-mean random error. The β parameter is the treatment effect of interest, indicating the marginal effect on the probability of escape of deploying LATs, all else equal.

The parameters in equation (1) could be estimated directly using ordinary least squares (or using a distributional link function such as probit or logit) if the assignment of LATs was plausibly random. But casual observation suggests that LATs are not randomly assigned, and direct estimation of equation (1) would yield biased and misleading estimates of the treatment effect. Previous research on aviation effectiveness has observed that aviation resources tend to be assigned to fires that are more likely to escape (Plucinski *et al.* 2012), which suggests that aircraft reduce suppression effectiveness or that aircraft are assigned to ignitions that are most difficult to contain.

If the non-random assignment of LATs is determined in part by factors that also affect the likelihood of initial attack escape, then LAT assignment (and the variable T_i in equation (1)) is endogenous. Endogeneity would account for observations of ignitions with aviation deployment being more likely to escape than those that do not receive aviation resources. It could be that managers can recognize ignitions that have a high potential to grow rapidly and cause damage, and seek to use aviation resources to respond quickly and contain the ignition. In this case any effectiveness of aviation on the likelihood of containment would be (at least in part) masked by the fact even without treatment ignitions receiving aviation are more likely to escape than those that do not receive aviation resources.

To identify the LAT effect and estimate unbiased treatment effects we need to identify a factor that predicts whether an ignition will be assigned a LAT but is unrelated to the likelihood of escape. That is, we need to find a variable Z that satisfies,

(3) $T_i^* = \theta + \delta Z_i + \varepsilon_i$,

(4) $T_i = \begin{cases} 1\ if\ T_i^* > 0 \\ 0\ if\ T_i^* \leq 0 \end{cases}$'

(5) $E[Z_i \mu_i] = 0,\ E\left[Z_i \varepsilon_{i_i}\right] = 0$.

The structural equations formulation of an endogenous treatment variable is a common general way to express the relationships between treatment, outcomes, and identification of the treatment effect (Angrist *et al.* 1996; Chiburis *et al.* 2012). For estimation purposes the primary challenge is to specify a valid identification strategy for T_i that satisfies equation (5).

Model with heterogeneous effects

Although the average treatment effect (ATE) of deploying air tankers to new wildfire ignitions is relevant for policy and planning decisions, from an operational standpoint it is important to understand the conditions under which LATs may (or may not) be effective. Wildfires may ignite under greatly varying fire environment conditions, including weather, topographic, vegetation, and geographic conditions. Understanding how these conditions relate to LAT effectiveness can help managers make informed decisions about LAT deployments.

We extend the basic structural model in equations (1) – (5) to incorporate treatment heterogeneity in a simplified way. Our approach is related to the notion of "essential heterogeneity," where the treatment effect (in this case the effect of LAT deployment on fire containment during initial attack) varies with observed or unobserved factors that are related to the likelihood of receiving treatment (Heckman *et al.* 2006; Xie *et al.* 2012).

To explore heterogeneity we hypothesize that there is a range of fire environment conditions where LATs may be effective, and that outside of this range LATs are mostly ineffective. More specifically we posit that LAT effectiveness may be different when the fire environment supports rapid fire growth and high fire intensity (e.g., high winds, low humidity, steep terrain, and dense vegetation), limited fire spread and low fire intensity (e.g., low winds, high humidity, flat terrain, and sparse vegetation), or moderate fire spread and intensity. If LAT effectiveness is different for these different fire environment conditions, then managers may be able to target LAT deployments to maximize effectiveness and avoid LAT use when the containment benefits would not likely justify the exposure of firefighters to hazards and costs.

A simple way to incorporate heterogeneity is to include in the analysis a contextual variable thought to be related to the treatment effect interacted with the treatment variable (Vivalt 2015). In an impact analysis contextual variables can summarize whether an observed effect changes under different circumstances. The contextual variable, particularly for wildfire initial attack conditions, could be thought of as a measure of the propensity of receiving treatment. If treatment propensity is related to treatment effectiveness the estimated ATE will be unbiased but may ignore useful information about heterogeneous treatment effects.

We follow a modified version of the propensity score-stratification method of examining heterogeneity in Xie et al. (2012). In this case we consider a measure of fire growth potential at the time of fire ignition as a measure of treatment propensity. The rationale is that fire managers may make tactical decisions about LAT deployment based on expected fire growth and behavior, but that these conditions are also related to the likelihood that a fire escapes initial attack efforts. If treatment assignment is identified (i.e., we are able to satisfy equations (3)-(5)), then estimating the treatment effect for fires stratified by fire growth potential can indicate how the treatment effect varies across strata.

Using a measure of fire growth potential as an indicator of treatment propensity (p_i), we define $j \geq 2$ strata such that p_i is homogenous within strata but varies between strata, or $Var\left(p_{ij}\right) < Var\left(p_{iJ}\right)$. Treatment effects are estimated using equations (1)-(5) for each of the strata, with the null hypothesis that $\beta_j = \beta_k \forall\, j \neq k$.

Empirical strategy

In this study, we examine effectiveness of large air tanker (LAT) deployments on the success of initial attack efforts. The use of LATs to deliver water or chemical retardant to new fire ignitions is a common method used to limit the size of fires during initial attack. Initial attack is typically considered successful if the fire is controlled before it reaches some specific size. For this study, we define initial attack success as containment of the fire before it reaches 300 acres (121 hectares), which is consistent with the USDA Forest Service measures of initial attack performance (USDA Forest Service 2018).

Methods

The goal of the empirical approach is to identify the average treatment effect of LAT drops on the likelihood that initial attack is successful for a given ignition. The outcome variable (*ia_success*) and treatment variables (*lat_drop*) are both binary variables. The standard approach for analyzing such binary outcomes is probit or logistic model. However, LATs are not likely randomly assigned to new ignitions; fires that are more difficult to manage are more likely to receive LATs and fires that involve the use of LATs are more likely to escape. Because LAT use and initial attack success are jointly determined, the traditional probit model might be inadequate. We address the endogeneity issue by attempting to identify appropriate instrumental variables to estimate a recursive bivariate probit model, and by estimating a semiparametric bivariate probit model without traditional instrumental variables.

One main difficulty of estimating recursive bivariate model is identification of a valid instrument that is significant determinant of treatment variable but does not directly influence outcome variable. A valid instrument for our application needs to have a causal effect on the LAT use but should not directly influence initial attack success. We identified and used daily number of uncontained large fires (*uncontained_lf*) as a potential instrumental variable to account for endogeneity. We argue that the number of large and uncontained fires may influence on the availability of LATs for deployment on new ignitions on that specific day. However, the number of uncontained large fires will not likely affect the growth potential of new ignitions or the operational capability of initial attack efforts.

We also explore a semiparametric bivariate probit model to examine the effectiveness of LAT drops on initial attack success. Marra and Radice (2012) suggest that a semiparametric bivariate model can be estimated in the absence of instrumental variable under certain assumptions. This approach allows us to model the functional dependency of the response variable on continuous covariates in the presence of endogeneity. A penalized maximum likelihood method is used to estimate the semiparametric version of the bivariate probit model to capture the effects of non-linear covariates.

Finally, also examine whether the effectiveness of LAT deployments are heterogeneous. For example, it is possible the use of LATs might be effective for fires within a moderate range of potential fire size, but less effective for expected complex and large fire (Keating *et al.* 2012; Calkin *et al.* 2014). To examine potential heterogeneous treatment effects, we grouped fires in the sample based on a measure of fire growth potential into three groups. Growth potential is measured as the modeled size of fires after four burning periods the Near Term Fire Behavior (NTFB) model, a deterministic implementation of the FSPro ensemble fire simulation method (Finney *et al.* 2011). Fires in the data sample were divided into three different groups – small, medium, and large modeled size – such that each group contains one third of the sample.

Data description

Data from this study was collected from several sources. Observations of fire ignitions managed by the USDA Forest Service (USFS) in 2010, 2011, and 2012 were drawn from records contained in the Wildland Fire Decision Support System (WFDSS). LAT drops were identified from the Operational Loads Monitoring System (OLMS) installed onboard the LAT fleet (Stonesifer *et al.* 2016). Data on final fire size were collected from Fire Occurrence Dataset (FOD) for the fire that burned in the United States between 2010 and 2012. Weather related information was collected after linking LAT drop data with fire location data set including FIRESTAT, SitReport, Firecode, WFDSS, Geospatial Multiagency Coordination (GeoMAC) and state fire records. Expected size of the fires were estimated using the Near Term Fire Behavior (NTFB) model. NTFB uses topography, fuel, weather, and wind to model fire growth. For the fires in the data set NTFB was run on actual weather conditions that were observed at the time of ignition. Output from NTFB includes modeled fire growth (in acres) during each of the four burning periods following ignition and total modeled fire size after four periods. Observations of ignitions from WFDSS paired with LAT drop data and NTFB outputs were matched with records from the FOD (Short 2014) to observe actual final fire size and duration (from discovery to containment).

The resulting data set includes 11,800 ignitions during the 2010-2012 study period. Of these 199 received at least one LAT drop during the first operational period.[5]

The outcome variable *ia_success* is equal to one if the final size of the fire is less than 300 acres. Treatment variables *lat_drop* is equal to one if the fire received at least one LAT drop. Effectiveness of suppression resources depends on a variety of factors such as fire characteristics, weather characteristics, geospatial characteristics etc. Exogenous variables used in the analysis are geographic area indicators, national preparedness level (a measure of overall fire activity), calendar quarter of ignition, energy release component (ERC, a measure of the fuel moisture conditions; higher relative values of ERC on a 0-100 scale indicate drier and more flammable conditions), a categorical indicator (low, moderate, high) of nationwide initial attack

[5] LAT drops during the first operational period (approximately the first day after discovery of the ignition) are defined as initial attack drops. Some fires received LAT drops but after the initial attack period (called extended attack); these are not included in the set of fires defined as receiving treatment of LAT drops during initial attack. See Stonesifer et al. (2016) for definitions and details on LAT use during initial and extended attack.

activity, estimated travel time from the ignition point to the nearest hospital (as a measure of remoteness), amount of other suppression resources assigned at initial attack, and the value of housing within a 10-mile radius of the ignition point.

Results

Descriptive statistics

Of the 11,800 wildland fires that ignited between 2010 and 2012 and were under Forest Service management responsibility, 97.42% of fires were contained before reaching an area of 300 acres (Table 1). The success rate for fires that did not receive is 96.46% and success rate for fire that receive LAT is 57.3%. The substantially lower success rate associated with the fires that received at least one LAT drop demonstrates that the fires that receive LATs tend to be more complex and more likely to escape.

[Table 1. about here]

Descriptive statistics and definitions of the variables included in the analysis are presented in Table 2. The vast majority of ignitions were contained before the fires reached a size of 300 acres. Overall, 2% of the fire received at least one LAT drop (*lat_drop*).

[Table 2 about here]

Naïve, recursive bivariate probit and semiparametric bivariate probit model results

We analyzed data using naïve probit, bivariate probit and semiparametric bivariate probit models. We started with standard probit analysis. Then we identified and used an instrumental variable to examine the impact of LAT drops on IA success using recursive bivariate probit model. We also used semiparametric bivariate probit model. Finally, we divided the sample into three different size group to examine if the impact is different for different fire size group. Naïve probit, bivariate probit model and semiparametric bivariate probit model results are presented in Table 3.

[Table 3 about here]

Naïve probit model results (column1, Table 3) indicate a negative relationship between LAT deployments and likelihood of initial attack success, consistent with the much lower overall success rate among fires that received LAT drops. Because we suspect that *lat_drop* is endogenous – in particular that fires more likely to escape are more likely to receive LAT deployments – the estimated treatment effect in the naïve probit model are likely downward biased.

To address the endogeneity problem, IA success and LAT drops were jointly estimated using bivariate probit model. The bivariate probit model allows us to better identify the LAT treatment effect with an instrumental variable that predicts LAT deployment but not likelihood of initial attack success. Number of active and not yet contained large fires (*uncontained_lf*) was used as an instrumental variable. The number of uncontained large fires may predict LAT deployment because ongoing large fire incidents typically command large resource commitments that may limit the availability of LATs on new ignitions. The estimated parameters of the instrumental variable in the treatment equation is negative and significantly different from zero indicating that the likelihood of a fire receiving LAT is less when there are more larger fire that are still uncontained and suggesting that *uncontained_lf* is a valid instrument.

The bivariate probit model, controlling for the likelihood of receiving a LAT, suggests that the average effect of LAT deployment on initial attack success is not significantly different from zero. Whereas the naïve probit indicated negative and significant effect of LAT drops, the downward bias mostly disappears with the instrumental variable approach.

It is possible that some of the continuous variables may have non-linear functional relationships with the response variable. A classical bivariate probit mode does not allow us to estimate such flexible functional dependence (Marra and Radice 2012). We estimated a semiparametric bivariate probit model to control for the potential non-linear relationship of some of the continuous variables in the presence of endogeneity. Semiparametric model results are presented in third column of Table 3. Similar to the bivariate probit with instrumental variables, the treatment effect for LAT drops is negative but not statistically different from zero. Two continuous variables (*rescapacity* and *value_10mi_m*) were used as nonparametric components using smooth functions in the semiparametric bivariate model. Effect of all other exogenous variables are consistent across three different models.

Bivariate Probit results for different fire size

It is possible that the estimated average treatment effects mask heterogeneity among different types of fires in the effectiveness of LAT deployments. To examine the possibility of heterogeneous effects of LAT drops on initial attack success for fires with different growth potential, we estimated the bivariate probit model using instrumental variables for fires grouped by modeled growth potential. Final modeled fire size after four burning periods estimated from a fire behavior model (NTFB) was used to divide the sample into three groups such that there are equal number of fires in each group. Results for the three groups are presented in Table 4.

[Table 4 about here]

The estimates of the treatment effect by growth potential group indicate that LAT deployments are not equally effective for fires with different potential to grow large. The estimated treatment effect is positive and statistically significant for ignitions with moderate growth potential, but is negative (and marginally significant) for ignitions with low growth potential and not statistically different from zero for ignitions with high growth potential. This result implies that likelihood of IA success increase because of LAT use for the fires that that have medium growth potential. Results also suggests that the use of LAT might not be as effective for the fires that are expected to grow significantly large.

The results suggest that LATs may help contain ignitions that are expected to have moderate growth potential, but no effect on ignitions with either very high or minimal growth potential. The estimated treatment effect implies that deploying LATs to ignitions with moderate growth potential in the sample increased the likelihood of containment during initial attack by 8.54 percentage points.

Discussion

The main objective of the paper was to examine the effect of large air tanker (LAT) deployments to wildfire ignitions on the likelihood that ignitions are successfully contained during initial attack. The econometric estimates provide evidence that LAT deployments may be effective for the group of fires with moderate growth potential. But LAT deployment was not associated with higher likelihood of containment among ignitions with either limited or very high growth potential.

There are several limitations to consider when interpreting the results. For example, the modeled growth potential used to categorize fire into three different groups was obtained using a simulated fire behavior model (NTFB). Our analysis is subject to uncertainty associated with the fire size produced by the fire behavior model. Any uncertainty or error associated with the models might influence our result. Also, endogeneity of LAT deployments remains a challenge; although an instrumental variable approach and a semiparametric approach appear to help identify the LAT effect, we cannot rule out the possibility that the estimated treatment effects suffer from remaining endogeneity bias.

Finally, it is important to note that the analysis only considers a narrow definition of LAT effectiveness, i.e., that success during initial attack is defined as containment below a fire-size threshold. Although this definition is consistent with how public agencies report performance for initial attack, it is possible that other definitions of initial attack success are relevant (e.g., containment within a time duration) or that other objectives of LAT use could be important. For example, LATs could be used to prevent fire growth along a portion of the fire to prevent damage to communities, but not target containment of the entire fire perimeter. In such cases we do not observe instances of success or failure, and thus could be mischaracterizing the effectiveness of LAT deployments. Further research, particularly with detailed operational information, is necessary to investigate all of the objectives and outcomes associated with LATs.

The econometric model of initial attack success shows promise for providing managers with timely information about the chance that a new ignition will grow to be a large fire and the likely effect of deploying LATs during initial attack. But the overall margins for improvement are small (given that the vast majority of ignitions do not become large first). Further research is needed to predict the likelihood that an ignition will be costly or cause significant damage. The analysis of LAT deployments suggests that it may possible to identify ignitions where the timely assignment of an LAT improves chances of initial attack success. Identifying these ignitions may allow managers to assign LATs to ignitions where marginal benefits will be greatest, thus improving the cost effectiveness of initial attack and LAT use. Yet, the evidence on LAT effectiveness at initial attack remains limited; further research may be necessary to explore other fire management tactics that may be effective at reducing the damage and costs associated with large fires.

References

Angrist JD, Imbens GW, Rubin DB (1996) Identification of causal effects using instrumental variables. *Journal of the American statistical Association* **91**(434), 444–455.

Arienti MC, Cumming SG, Boutin S (2006) Empirical models of forest fire initial attack success probabilities: the effects of fuels, anthropogenic linear features, fire weather, and management. *Canadian Journal of Forest Research* **36**(12), 3155–3166.

Calkin DE, Stonesifer CS, Thompson MP, McHugh CW (2014) Large airtanker use and outcomes in suppressing wildland fires in the United States. *International Journal of Wildland Fire* **23**(2), 259–271.

Chiburis RC, Das J, Lokshin M (2012) A practical comparison of the bivariate probit and linear IV estimators. *Economics Letters* **117**(3), 762–766.

Donovan GH, Prestemon JP, Gebert K (2011) The effect of newspaper coverage and political pressure on wildfire suppression costs. *Society & Natural Resources* **24**(8), 785–798.

Finney MA, Grenfell IC, McHugh CW, Seli RC, Trethewey D, Stratton RD, Brittain S (2011) A method for ensemble wildland fire simulation. *Environmental Modeling & Assessment* **16**(2), 153–167.

Hand MS, Wibbenmeyer MJ, Calkin DE, Thompson MP (2015) Risk preferences, probability weighting, and strategy tradeoffs in wildfire management. *Risk analysis*.

Heckman JJ, Urzua S, Vytlacil E (2006) Understanding instrumental variables in models with essential heterogeneity. *The Review of Economics and Statistics* **88**(3), 389–432.

Keating EG, Morral AR, Price CC, Woods D, Norton DM, Panis C, Saltzman E, Sanchez R (2012) “Air Attack Against Wildfires.” (Rand Corporation)

Marchi E, Neri F, Tesi E, Fabiano F, Brachetti Montorselli N (2014) Analysis of helicopter activities in forest fire-fighting. *Croatian Journal of Forest Engineering: Journal for Theory and Application of Forestry Engineering* **35**(2), 233–243.

Marra G, Radice R (2012) A Semiparametric Regression Framework for Modelling Correlated Binary Responses. *Analysis and Modeling of Complex Data in Behavioural and Social Sciences* 58.

Morin AA, Albert-Green A, Woolford DG, Martell DL (2015) The use of survival analysis methods to model the control time of forest fires in Ontario, Canada. *International Journal of Wildland Fire* **24**(7), 964–973.

National Multi-Agency Coordinating Group (2018) 2018 National Interagency Mobilization Guide. National Interagency Coordination Center (Boise, ID). https://www.nifc.gov/nicc/mobguide/index.html [accessed May 16, 2018].

Plucinski MP (2013) Modelling the probability of Australian grassfires escaping initial attack to aid deployment decisions. *International journal of wildland fire* **22**(4), 459–468.

Plucinski M, McCarthy G, Hollis J, Gould J (2012) The effect of aerial suppression on the containment time of Australian wildfires estimated by fire management personnel. *International Journal of Wildland Fire* **21**(3), 219–229.

Short K (2014) A spatial database of wildfires in the United States, 1992-2011. *Earth System Science Data* **6**(1), 1–27.

Stonesifer CS, Calkin DE, Thompson MP, Kaiden JD (2014) Developing an Aviation Exposure Index to Inform Risk-Based Fire Management Decisions. *Journal of Forestry* **112**(6), 581–590.

Stonesifer CS, Calkin DE, Thompson MP, Stockmann KD (2016) Fighting fire in the heat of the day: an analysis of operational and environmental conditions of use for large airtankers in United States fire suppression. *International Journal of Wildland Fire* **25**(5), 520–533.

US Department Of The Interior (2018) Budget justifications and performance information, fiscal year 2018. US Department of the Interior, Wildland Fire Management, Washington, DC. https://www.doi.gov/sites/doi.gov/files/uploads/fy2018_wfm_budget_justification.pdf [accessed May 16, 2018].

USDA Forest Service (2018) FY 2019 budget justification. USDA Forest Service, Washington, DC. February 2018. https://www.fs.fed.us/sites/default/files/usfs-fy19-budget-justification.pdf [accessed May 16, 2018].

Vivalt E (2015) Heterogeneous treatment effects in impact evaluation. *American Economic Review* **105**(5), 467–70.

Wilson RS, Winter PL, Maguire LA, Ascher T (2011) Managing wildfire events: Risk-Based decision making among a group of federal fire managers. *Risk Analysis* **31**(5), 805–818.

Xie Y, Brand JE, Jann B (2012) Estimating heterogeneous treatment effects with observational data. *Sociological methodology* **42**(1), 314–347.

Table 1. Number of fires, LAT use and IA success (2010 -2012)

	Initial attack success (Final area of the fire is less than 300 acres)		
Treatment	Success (<300 acres)	Failure (>300 acres)	Total
No LAT	11,382 (96.46)	219 (1.86)	11,601 (98.31)
LAT	114(0.97)	85 (0.72)	199 (1.69)
Total	11,496 (97.42)	304 (2.58)	11,800 (100)

Numbers in the parentheses indicate percentages. All percentages are based on total number of fires in the sample.

Table 2. Definition and descriptive statistics and of the variables used in the analysis

Variables	Definition	Mean	Std. dev.	Max	Min
iasuccess_fod300	IA Success (1=Yes, 0=No)	0.97	0.16	1	0
lat_drop	IA LAT drop (1=Yes, 0=No)	0.02	0.13	1	0
ga_rm	GA is Rocky Mountain^1 (1=Yes, 0=No)	0.1	0.3	1	0
ga_sw	GA is Southwest (1=Yes, 0=No)	0.23	0.42	1	0
ga_sca	GA is Southern California (1=Yes, 0=No)	0.07	0.26	1	0
ga_nca	GA is Northern California (1=Yes, 0=No)	0.09	0.29	1	0
ga_nw	GA is Northwest (1=Yes, 0=No)	0.15	0.36	1	0
ga_nr	GA is Northern (1=Yes, 0=No)	0.13	0.34	1	0
ga_wb	GA is Western Basin (1=Yes, 0=No)	0.01	0.1	1	0
ga_eb	GA East Great Basin (1=Yes, 0=No)	0.12	0.33	1	0
npl_2	National preparedness level^2 is 2 (1=Yes, 0=No)	0.51	0.5	1	0
npl_3	National preparedness level is 3 (1=Yes, 0=No)	0.24	0.43	1	0
npl_4	National preparedness level^3 is 4 (1=Yes, 0=No)	0.14	0.35	1	0
ign_qtr2	Ignition quarter is 2 (1=Yes, 0=No)	0.19	0.39	1	0

ign_qtr3	Ignition quarter is 3 (1=Yes, 0=No)	0.73	0.35	1	0
ign_qtr4	Ignition quarter is 4 (1=Yes, 0=No)	0.06	0.39	1	0
ercg	Energy release component calculated from ignition point using nearest weather station (0-100 scale)	56.30	20.41	100	0
sitIA_mod	IA Situation is moderate (1=Yes, 0=No)	0.22	0.42	1	0
sitIA_high	IA Situation is high (1=Yes, 0=No)	0.04	0.21	1	0
htraveltime_12	Hospital travel time is 1 -2 hr	0.9	0.3	1	0
rescapacity	Productive capacity used during IA	50.39	185.7	6706	0
value_10mi_m	Housing value (million) within 10 mile	420.9	1838	56377	0

^1ga is the Forest Service geographical regions. Southern Region is used as a base category.
^2National preparedness levels, established by the National Multi-Agency Coordinating Group at National Interagency Fire Center, are dictated by burning conditions, fire activity, and resource availability. Resource availability is the area of most concern. Preparedness level ranges from 1 to 5; level 1 indicating virtually no fires and full availability of resources and level 5 indicating high fire activity in several geographical regions and limited resource availability.

Table 3. Naïve probit, bivariate probit and semiparametric bivariate probit model results

Variables	Naive Probit Model	Bivariate Probit Model	Semiparametric Bivariate Probit Model
(Intercept)	1.322*** (0.1901)	1.493*** (0.2003)	1.579*** (0.2185)
lat_drop	-1.558*** (0.1089)	-0.074 (0.3798)	-0.1561 (0.4048)
ga_rm	0.2361* (0.1301)	0.2053 (0.128)	0.006 (0.1384)
ga_sw	0.2617** (0.1153)	0.2415** (0.1152)	0.0279 (0.1247)
ga_sca	0.6487*** (0.1667)	0.7969*** (0.1665)	0.7097*** (0.17)
ga_nca	0.6648*** (0.1666)	0.7013*** (0.1664)	0.6112*** (0.1763)
ga_nw	0.6336*** (0.1445)	0.5996*** (0.144)	0.4747*** (0.1543)
ga_nr	0.1988 (0.1211)	0.1524 (0.1222)	-0.0268 (0.133)
ga_wb	0.6359* (0.3343)	0.6457** (0.316)	0.5757* (0.3379)
ga_eb	0.2487* (0.1334)	0.2707** (0.135)	0.0628 (0.1442)
npl_2	-0.0457 (0.1232)	-0.0621 (0.1203)	-0.094 (0.1281)
npl_3	-0.067 (0.13)	-0.0711 (0.1263)	-0.0766 (0.1347)
npl_4	-0.0317 (0.1461)	-0.0361 (0.1429)	-0.0629 (0.1514)
ign_qtr2	0.2552	0.2686	0.2644

	(0.1971)	(0.1975)	(0.214)
ign_qtr3	0.3276	0.3514*	0.2934
	(0.2103)	(0.2097)	(0.2266)
ign_qtr4	0.3248	0.3219	0.2375
	(0.2122)	(0.2121)	(0.2287)
ercg	-0.0039**	-0.0073***	-0.0043**
	(0.0017)	(0.0021)	(0.0022)
sitIA_mod	-0.0537	-0.0307	-0.0768
	(0.0685)	(0.0673)	(0.07)
sitIA_high	-0.0253	-0.0031	-0.0697
	(0.1405)	(0.0673)	(0.1461)
htraveltime_12	0.577***	0.5921***	0.643***
	(0.071)	(0.1411)	(0.0738)
rescapacity	-9e-04***	-0.0018***	-1.449
	(1e-04)	(1e-04)	(2.663)
value_10mi_m	1e-04**	1e-04**	1.038
	(0)	(0)	(4.254)
N	11,800	11,800	11,800

Significance codes: *** 0.01 ** 0.05 * 0.1
Numbers in parentheses indicate standard errors.

Table 4: Bivariate probit model results for small, medium and large group size fire

Variables	Bivariate Probit Small Group Size	Bivariate Probit Medium Group Size	Bivariate Probit Large Group Size
(Intercept)	1.949*** (0.3515)	1.525*** (0.4607)	1.113*** (0.363)
lat_drop	-1.38* (0.7438)	0.759*** (0.0824)	-0.23 (0.7192)
ga_rm	-0.0506 (0.2219)	0.4542** (0.212)	0.3693 (0.2939)
ga_sw	0.171 (0.2059)	0.5148*** (0.1914)	0.2608 (0.2757)
ga_sca	0.525* (0.3178)	0.7105*** (0.2503)	0.7133** (0.3264)
ga_nca	0.7622* (0.4509)	0.5442** (0.2209)	0.7709** (0.3254)
ga_nw	0.6364** (0.2836)	0.854*** (0.212)	0.4112 (0.1543)
ga_nr	-0.018 (0.2423)	0.2737 (0.1889)	0.3868 (0.2803)
ga_wb	3.713 (482)	4.961 (2198)	0.6919 (0.4207)
ga_eb	-0.039 (0.2444)	0.5632** (0.2239)	0.3901 (0.2968)
npl_2	-0.1677 (0.2561)	-0.2029 (0.2103)	0.0841 (0.1811)
npl_3	-0.0982 (0.2748)	-0.1783 (0.2201)	-0.0136 (0.1857)
npl_4	-0.1598 (0.2994)	0.3035 (0.2699)	-0.0618 (0.2085)
ign_qtr2	0.1762	0.0572	0.3179

	(0.363)	(0.483)	(0.2845)
ign_qtr3	0.2569	0.1236	0.4172
	(0.3823)	(0.4937)	(0.3111)
ign_qtr4	0.1783	-0.0558	0.907**
	(0.3702)	(0.4828)	(0.4438)
ercg	-0.0023	-0.0093***	-0.0069**
	(0.0037)	(0.0029)	(0.0033)
sitIA_mod	0.0239	0.023	-0.1168
	(0.1422)	(0.1098)	(0.1091)
sitIA_high	-0.4976**	0.1104	0.3191
	(0.2216)	(0.1098)	(0.2978)
htraveltime_12	0.2429	0.6165***	0.6773***
	(0.1643)	(0.2169)	(0.1099)
rescapacity	-0.0021***	-0.0014***	
	(3e-04)	(1e-04)	
value_10mi_m	3e-04**	2e-04	
	(1e-04)	(1e-04)	
N	3892	3896	4012

Significance codes: *** 0.01 ** 0.05 * 0.1
Numbers in parentheses indicate standard errors.