ARE REVENUES FROM ENERGY LEASES REINVESTED BY U.S. FARMS? EVIDENCE FROM TOTAL

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ABSTRACT

Farmland prices and agricultural production costs rose significantly over the last two decades, putting increasing pressure on farm operators and agricultural landowners to generate more revenue per acre. At the same time, millions of acres of U.S. agricultural land became attractive for energy development due to the shale gas revolution and rising demand for utility-scale solar and wind power. To its supporters, energy development on agricultural land is a win-win proposition, offering land-rich but cash-poor farm owners a new stream of income and, potentially, the means to relieve credit constraints and reinvest in their farms. Critics, however, fret that turning productive farmland over to gas wells and solar panels will contribute to long-term loss of agricultural land and raise the costs of farming in areas attractive for energy development.

At the crux of this debate are two still-unanswered or partially answered empirical questions: (1) what are the characteristics of farm businesses that choose to participate in energy leases and (2) what is the impact of energy leases on the long-term viability of host farms? This study uses national survey data from the USDA's 2014 Tenure, Ownership, and Transition of Agricultural Land (TOTAL) survey to shed new light on these issues. This large, rich, cross sectional data set provides an unprecedented perspective on farm financial behavior. In addition to detailed household and farm production characteristics, TOTAL collected detailed data on energy lease participation and income. Further, TOTAL included questions on whether a farm had difficulty accessing credit and made any capital or land investments. TOTAL contains other information not typically included in ARMS that may otherwise be unobservable, such as time to intended retirement or transition and

a risk preferences score.

This study uses stratified propensity score matching (PSM) to assess the impact of energy leases on participating farm businesses' capital investment, net income, and credit constraints. The TOTAL data set is exceptionally well-suited to analysis using PSM, allowing us to mitigate selection bias arising from systematic differences in the observable characteristics of farms that do and do not host energy projects. We can also contrast impacts associated with leasing oil or gas rights compared with other types of on-farm leases (for example hunting and renewable energy leases).

Our results suggest that energy production income is of minor importance to most of the farms that receive it. In particular, there is no evidence of an impact on credit constraints; farms with energy income were no more or less likely to report difficulty borrowing. We also found no significant effects on the amount of capital spending or overall net farm income. That said, farms with energy income were significantly more likely to report some capital investment (of any amount) and were significantly less likely to have negative net farm income.

BIOGRAPHICAL SKETCH

Travis A. Grout is a Master of Science candidate at the Dyson School of Applied Economics and Management at Cornell University. He worked for seven years in the U.S. Department of State as a Foreign Service Officer prior to attending Cornell. Thrice awarded for exemplary service, Grout played an important role in rewriting U.S. textile trade preferences for Haiti after its 2010 earthquake; managed a Seoul office assisting U.S. citizens during a North Korean invasion scare; wrote and edited portions of the U.S. government's environmental review of the proposed Keystone XL pipeline project; and represented the National Oceanographic and Atmospheric Administration (NOAA) in international environmental and scientific meetings. Seeing a need for more rigorous economic analysis in government, he left the Department of State in 2016 to study applied economics.

Travis's wife, Liz Fabis, is also a Cornell University graduate student, pursuing a Masters of Landscape Architecture. They live in Ithaca with their three lovely kayaks, two lovely cats, and one lovely expresso machine.

This thesis is dedicated to my wife and family. Thanks for your patience and love, even when I talk about economic models at Thanksgiving.

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I am also indebted to Dr. Miguel Gomez. The initial inspiration for this project came from a short research paper on solar incentives that I completed for Dr. Gomez's excellent consumer economics course. Later, his help was invaluable while developing a model for this study.

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Finally, a few words of thanks to my fellow graduate students, who were always willing to help work through a methodological problem, proofread a complicated chapter, or just commiserate over a beer at the Big Red Barn. The Dyson graduate program prides itself on recruiting superb scholars, but those in my cohort also happen to be superb people. To Prankur Gupta, Christine Stephan, Anjali Narang, and my other fellow students: thanks for everything.

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CHAPTER 1

INTRODUCTION

It is tempting to think of the countryside as something timeless, a place isolated from (if not antithetical to) industrialization. However, energy development on farmland is as old as U.S. energy industries themselves. Hamilton McClintock of Cornplanter Township, Pennsylvania may have been the first American farmer to sign an oil lease in 1859, just months after the first U.S. oil well started production (Hill, 2011). The nation's first large-scale electrical power plant, George Westinghouse's famous hydroelectric station at Niagara Falls, had great difficulty persuading farmers to sell land for a 30-foot-wide transmission corridor; the final route's loops and detours reflect dozens of compromises with landowners unwilling to give up productive cropland or demanding a route that skirted, rather than cut across, their fields (Dunlap, 1896). Later, farmland leases played a role in the birth of renewable electricity industries: rancher Hugh Walker leased the land for the United States first utility-scale wind farm at Altamont Pass (Sussman, 1981). A cursory glance through the historical record finds that contemporary questions about energy development on farmland–the importance of energy royalties to struggling farms (United States Senate, 1980), damage to farmland due to energy production (Bennett, 1968), risks assumed by farmers with an energy lease (Castleberry Jr, 1957), disruption to local agricultural economies (Parcher, 1947), and impacts on farmland prices (Salisbury, 1941)–have been matters of concern and study for generations.

That said, the pattern and the pace of energy development on agricultural land has changed dramatically over the last decade. Improved hydraulic fracturing (fracking) and horizontal drilling techniques revolutionized the U.S. oil and gas industries, allowing profitable exploration of vast oil- and gas-bearing shale formations. These technological advances triggered a rush by drilling firms to secure exploration and extraction leases, often in areas with little history of oil and gas production. Between 2000 and 2012, almost 7 million acres of pasture and cropland were converted into drilling pads and associated infrastructure (Allred et al., 2015), an area slightly larger than Massachusetts. A decade into large-scale unconventional oil and gas production, its impact on participating farms and local agricultural economies is still a matter of intense debate.

The last decade also saw a dramatic drop in the cost of wind and solar power that, in conjunction with widespread development incentives, prompted rapid growth in generating capacity. From 2008 through 2017, net generation from U.S. wind power grew by 359%. Utility-scale solar generation grew an incredible *6029%* over the same period (U.S. Energy Information Administration, 2018b). Despite disagreement about the likely pace of expansion, most mainstream projections anticipate that U.S. wind and solar power will continue to grow over the the coming decades (Heinrich et al., 2015; U.S. Energy Information Administration, 2018a). In the long term, this expansion may have even greater implications for rural landowners than the shale gas revolution. Compared to the total area of the United States, the amount of land that will be affected by renewable energy expansion is trivial; however, that growth is likely to disproportionately affect farmland. The ideal tract of land for solar development is flat, dry, unshaded, close to transmission infrastructure and customers, accessible to installers and maintenance, with few near neighbors, and in an area with high solar radiation. All of these characteristics are associated with farmland. Proximity to existing infrastructure is even more important for wind development, a key reason why 93% of U.S. wind power is located on rangeland or cropland (Xiarchos and Sandborn, 2017).

To its supporters, energy development is an obvious win-win proposition, allowing land-rich but cash-poor producers to gain a new stream of income in exchange for a small percentage of an area's farmland. Critics, however, fret that turning productive farmland over to gas wells and solar panels will contribute to a long-term loss of agricultural land and raise the costs of farming in areas attractive for energy development. In this context, it is important to ask those old questions about conflicts between agricultural and energy stakeholders again, taking into account new realities about how and where energy development is taking place. A better understanding of the effects of energy development on both participating farms and local agricultural economies can contribute to better outcomes for farmers, planners, and energy companies alike.

1.1 Research objectives

This thesis contributes to the literature on rural energy development by answering two key questions.

First, what are the characteristics of farm businesses that choose to participate in energy leases? We use logistic regressions to identify attributes of farm businesses associated with a greater or lesser likelihood of reporting energy production income. To adequately address this issue, we also test for differences in how different sizes and types of farms respond to local energy development and examine whether the the characteristics of farms with oil or gas leases differ from those of farms leasing land for other non-agricultural purposes.

Second, what are the impacts of energy leases on the long-term viability of host farms? We use propensity score matching to isolate the impacts of energy lease income on capital investment, net farm income, and credit constraints. Again, we run variations of our model to test for differences across broad types of farms and between farms receiving oil and gas income vs. other lease income.

1.2 Methods and organization

This study uses confidential farm-level data from the USDA's 2014 Tenure, Ownership, and Transition of Agricultural Land (TOTAL) survey. The National Agricultural Statistics Service, in collaboration with the USDA Economic Research Service, used TOTAL to gather data on agricultural landowners' income, expenses, debt, assets, and demographic characteristics. While similar to the annual Agricultural Resource Management Survey (ARMS), TOTAL collected much more detailed financial information than ARMS and did not focus on specific commodities. It is part of the U.S. Census of Agriculture.

To identify the characteristics of farms that choose to participate in energy leases, we use a series of logistic regressions with sampling weights provided by the USDA and errors clustered by state. The base specification uses a simple binomial outcome variable reflecting whether a given farm reported *any* income from energy production. We then repeat the regression with two alternative outcome variables reflecting whether the given farm received *significant* income from energy production, defined as as 50% of of net farm income (specification 2) or total energy income above \$10,000. These variations test the robustness of our conclusions and provide additional insight into the factors driving farms' decisions on energy development.

After applying sampling weights, outcomes from the above specifications should reflect the population of U.S. farm owner-operators. However, this is not our only population of interest. The 3-category USDA typology used in TOTAL defines 60% of U.S. farms as "residence" family farms that are (1) operated by a part-time or retired farmer and (2) have less than \$350,000 in annual gross cash farm income (GCFI) (Hoppe and MacDonald, 2013). Although the majority of U.S. farms are residence operations, they represent just 6.2% of U.S. agricultural production by value. "Commercial" farms (family farms with GCFI over \$350,000 and all nonfamily farms) or "intermediate" farms (full-time farmers[1] with GCFI under \$350,000) produce 79% and 14.8%, respectively, of U.S. agricultural value. Since intermediate and commercial farms are disproportionately important to the U.S. agricultural economy, we repeated the regressions above while omitting residence farms from the sample.

Next, we ran a series of regressions to tease out differences in the characteristics of farms participating in oil and gas leases compared to other types of non-agricultural leases. We used two simple binary outcome variables reflecting whether a given farm (1) had leased oil or gas rights for *any* land owned by that operation and (2) had leased other rights on land owned by the operation.

[1]More precisely, farms in the intermediate category have primary operators who report farming as their primary occupation.

Having identified characteristics of farms participating in energy leases, we assess the impacts of energy lease income on participating farms using propensity score matching. For each of the 29,733 farms in the TOTAL sample, we estimate the likelihood that a farm with its known characteristics would be in the treatment group for each of the outcome variables described above. The resulting propensity scores allow us to match each treated farm with a similar untreated operation (a "nearest neighbor" algorithm) and compare outcomes in terms of capital investment, net farm income, and credit constraints.

Following this introductory chapter:

Chapter 2 reviews prior research into the characteristics of farms leasing land for energy development and the effect of energy leases on farm businesses. We also draw on the relevant literature on off-farm income, farmers' propensity to invest income from various sources, and prevalence and effect of credit constraints on U.S. farms.

Chapter 3 describes the data used in this paper. The principal source is the USDA's 2014 TOTAL survey, but this is complemented by data collected by the U.S. Census Bureau and others.

Chapter 4 lays out theoretical frameworks for participation in an energy lease and for impacts of energy income on farm viability, followed by a description of the empirical models used in this thesis.

Chapter 5 relates the results of analysis of the characteristics of farms that choose to participate in energy leases, looking at all U.S. farms and several populations of interest.

Chapter 6 lays out the results of analysis on the effects of energy lease income on participating farms.

Chapter 7 summarizes findings and delves into the implications for farmers, energy developers, and policymakers. It also highlights unanswered questions and suggests avenues for future research.

CHAPTER 2

LITERATURE REVIEW

2.1 Renewable energy development on farmland

Within the broader literature on renewable energy siting, at least three studies using data from the USDA (NASS) 2009 On-Farm Renewable Energy Production Survey (OFREPS) have analyzed factors influencing farms' adoption of solar or wind technology[1]. Xiarchos and Lazarus (2013) found a strong positive correlation with energy prices, organic acres per farm, rural internet connectivity and, for solar adoption, farmer tenure. The authors observed a negative correlation with market share of electric cooperatives (which are exempt from some relevant state and federal regulations). Of state policies considered, only renewable portfolio standards (RPS) appeared to stimulate adoption by farms. Beckman and Xiarchos (2013) used a double-hurdle model to examine the characteristics of farms that installed a PV system of any size in California and, among adopters, traits associated with relatively large (or relatively small) systems. Farms with commercial-scale PV systems (as opposed to those intended primarily for on-farm consumption) had:

- More capital investment (twice the average value of machinery);
- Fewer total acres, but more valuable farmland (both in terms of per-acre value total property value);
- Operators with more years of agricultural experience;

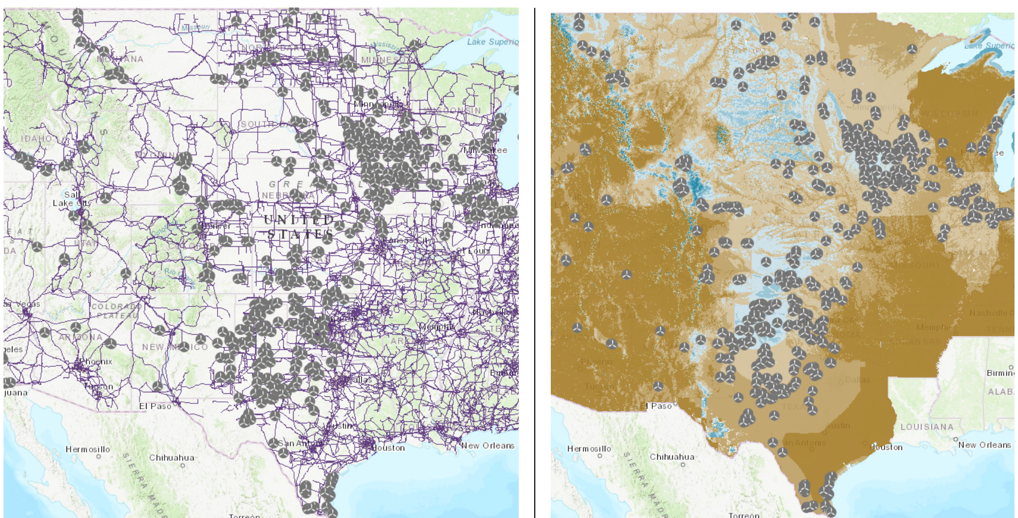
[1]Note that OFREPS did not collect data on wind generating facilities of 100kw or greater nameplate capacity.

- Greater reliance on farm income as a percentage of the household budget; and,
- Greater energy consumption (in terms of $ /year).

In a nationwide study the following year, Borchers et al. (2014) found that state-level net metering and interconnection policies favoring small electricity producers effectively promoted renewable energy installation on farms; cost incentives (e.g., grants, rebates, and tax credits) and state renewable portfolio standards seemed to have little, if any, impact in this regard.

Fewer studies specifically address wind development on U.S. farms, likely because wind leases are less common than solar and because wind turbines are easier to colocate with continued agricultural production than utility-scale solar. NREL estimated that the average U.S. wind farm directly and permanently affected just .75 acres per MW in capacity (Denholm et al., 2009) compared to 7.3 acres directly affected per MW for large-scale solar (Ong et al., 2013). Access to transmission infrastructure remains a substantial challenge for wind developers. To a greater extent than for solar development, the country's most productive locations for onshore wind turbines (typically open plains or exposed uplands) are often sparsely settled and remote from population centers (Brown et al., 2017). The pattern of wind farm expansion on the Great Plains has followed transmission infrastructure as much as wind resource quality. North Texas offers an excellent case study, as its Competitive Renewable Energy Zone (CREZ) transmission network enabled the state to greatly outpace wind capacity growth in states with comparable wind resources (Orrell et al., 2016). Based on interviews with 23 Scottish farmers applying for wind development permits, Sutherland and Holstead (2014) reported that participating farmers saw wind power primarily as a diversification strategy. While many farms in the area had exploitable wind resources, the farmers actively pursuing development were disproportionately owner-operators with large landholdings. The authors also stressed up-front permitting costs and opposition from close neighbors as significant barriers to development on smaller farms.

Figure 2.1: **Great Plains wind farms mapped on wind resources and transmission lines**



Utility-scale wind farms mapped on major long-distance transmission lines.

Wind farms and wind resource quality, using a scale of poor (darkest brown) to superior (darkest blue) wind resources.

Created using the Energy Information Agency's U.S. Energy Mapping System.

Since local support or opposition has a strong impact on the speed and cost of wind development (Chen and MacDonald, 2011), it is also important to consider key predictors of local opposition to wind farms. Public attitudes toward wind farms influence whether and where farmland will remain attractive for wind development, as well as the benefits of development for landowners. Studies of attitudes toward wind power in the United

States suggest that greater proximity to a *proposed* wind farm site is correlated with more negative attitudes toward the project; however, this effect is not apparent for active wind farms (Swofford and Slattery, 2010; Jacquet, 2012; Slattery et al., 2012). There is some evidence that support for local wind farm development is tied to expectations that wind power will support local economic growth, even for individuals who do not expect to benefit personally Slattery et al. (2012); Brannstrom et al. (2011). The perceived scenic value of the wind farm site (and perceived aesthetic appeal of wind turbines) also seem to be significant (Groothuis et al., 2008). Residential real estate values near proposed and operating wind farms may be a useful proxy for local acceptance of wind development. The most comprehensive U.S. study of the effect of wind development on property values is Hoen et al. (2011), which drew on data for almost 7,500 sales near U.S. wind farms and found no significant effects associated with proximity to or views of wind turbines.

Bigelow et al. (2016) used TOTAL data and a discrete choice model to identify attributes of non-operating agricultural landlords associated with higher (or lower) propensity to exercise non-agricultural (secondary) use rights on farmland that they owned. The study examined predictors for several specific non-agricultural uses, including oil and gas leases and wind leases. The researchers found that landlords were more likely to lease wind rights if they allowed their tenants to make decisions regarding government program enrollment (possibly indicating that the landlord has less day-to-day involvement with farm management); if the rented land was in a county with high wind potential; and, curiously, if the farmland was leased (at least in part) for a share of its agricultural production. There was no significant relationship between wind leases and per-acre agricultural rent, corporate ownership, or landlords residing in a different county than the rented farmland.

In addition, there are many works on the identification of land for solar development more generally and willingness of landowners to participate. A 2015 study produced a system for estimating the suitability of a given parcel of land based on environmental and social constraints (Brewer et al., 2015). Brewer et al. inferred desirable physical characteristics for siting from the location of existing solar installations with greater than 1 MW capacity. Social constraints were derived from a survey on public attitudes toward buffer zones between solar farms and agricultural, residential, and other land types. Combined, these models identify parcels likely to be technically, financially, and socially acceptable for solar development. Carlisle et al. (2016) emphasized the visual impact of proposed solar facilities, and found that public support varied considerably depending on a parcel's current land use and the size of a buffer between the project site and land deemed to be socially or environmentally valuable (e.g., recreation areas and wildlife breeding grounds).

There may be similarities between farms that are willing to retire land for renewable energy development and those participating in long-term conservation investments such as the Conservation Reserve Program (CRP). Both Claassen and Morehart (2009) and Soule et al. (2000) found that low-tenure farmers (those who own a relatively small percentage of the land that they farm) were significantly less likely to enroll in the CRP or to adopt farming practices promoting long-term productivity of the soil. However, Soule et al. state that share-renters may have more incentive and opportunity to participate in conservation practices, noting that they are no less likely than owner-operators to use conservation tillage while cash renters are significantly less likely to do so.

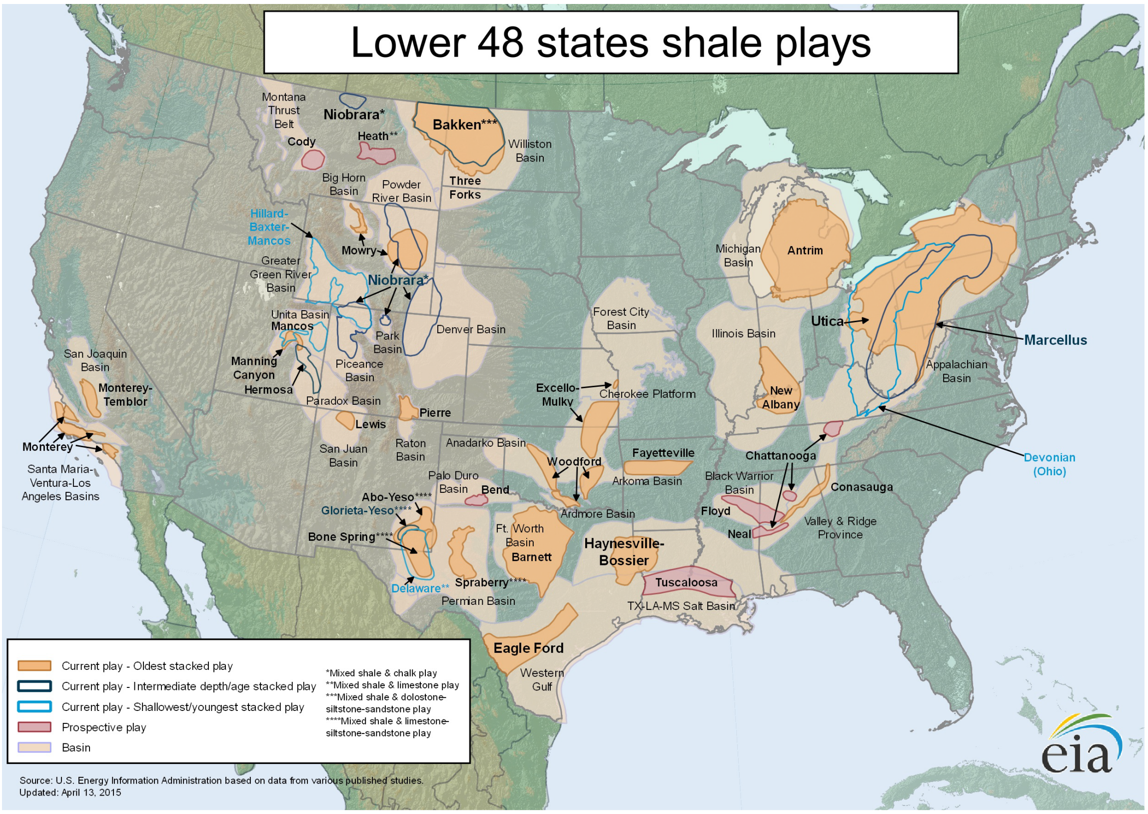
2.2 Oil and gas development on farmland

Many farmland owners have clearly benefited from the shale boom of the last decade, as many shale-bearing formations lie under productive agricultural regions (see Figure 2.2). By 2012, 35% of active U.S. farm and ranch land was in a county producing oil or gas from a shale play (Hitaj and Suttles, 2016). In areas conducive to shale gas development, farmers receive more income from energy leases and royalties than from government farm payments (Brown et al., 2016). Weber et al. (2013) estimated that the average farm household receiving revenue from an energy lease (most commonly oil and gas) gained $104,000 in net worth and that energy royalty payments to farmers totaled $2.3 billion in 2011. These payments were, however, highly concentrated among farmers; the median annual payment was just $7,000.

In a study of the terms of oil and gas leases in 16 states, Brown et al. (2016) found substantial variation in the average royalty rate (from a low of 13.2% in the Marcellus to 21.2% in the Permian play). Interestingly, royalty rates are only weakly correlated with resource abundance at a given site; the land leasing market for gas development is far from perfectly competitive, likely due to uncertainty and asymmetries in the information available to rights holders and developers (Brown et al., 2016; Fish, 2011). Prior researchers have also found evidence of variation in lease and royalty rates based on owners attitudes toward development risks (Timmins and Vissing, 2014) and the concentration of minority households in an area (Vissing, 2015).

There is some evidence that farms' responses to local shale gas development vary

Figure 2.2: **Map of oil- and gas-bearing shale formations**



with farm operation size. Reporting on interviews with farmers in the Marcellus shale play, Malin and DeMaster (2016) suggested that smaller, financially marginal farmers were more likely to sign gas leases. Several lessors in their interviews reported that the income from energy leases made it possible for them to keep farming or to pay for household essentials like health insurance. Using 2007 and 2012 county-level data for the Marcellus shale region, Xiarchos (2017) found that farms in counties that hosted unconventional gas drilling spent more on capital and equipment. However, the study also found evidence that farming in those counties was more consolidated, with fewer but larger operations; the authors noted that the difference in capital and equipment spending could be the result of smaller farms ceasing operations.

Multiple studies suggest that oil and gas leasing in an area drives up per-acre property values. A 2013 study found that the per-acre value of an acre of farmland rose $2.60 for each $1 in energy lease payments received by the landowner (Weber et al., 2013). A 2015 study reported that per-acre farmland prices rose 48% in the Marcellus shale play in Pennsylvania (Weber and Hitaj, 2015). Farmland prices also rose in other major shale plays, though less dramatically. The authors hypothesized that the difference was due to an unusually low rate of split estates (subsurface mineral rights owned by a different entity than surface property) in the Marcellus. Xiarchos (2017) also observed faster growth in median farmland value between 2007 and 2012 within Marcellus region counties that contained unconventional gas wells. These conclusions are supported by research focusing on the impacts of shale gas development on land values more broadly (i.e., not confined to farmland). In a study of residential property sales in Pennsylvania and New York, Boslett et al. (2016) found that a ban on hydraulic fracturing in New York (largely blocking shale gas development in the state) led to 23% lower land values for parcels suitable for shale gas production.

The apparent impact of energy development on land prices suggests that farmers with the least to gain and most to lose from energy development may be those who depend on rented farmland. A study using 2014 TOTAL data found that nonoperating farm owners are 50% more likely to enter into oil and gas development leases than farm owner-operators (Hitaj et al., 2018). The likelihood is even higher if the landlord lives in a different county.

Similarly, in their study of land use decisions by single-tenant agricultural landlords (see previous section), Bigelow et al. (2016) found that geographically distant landlords and those with share-based agreements with their tenant were more likely to lease oil and gas rights. Landlords were less likely to sign such leases for higher-value farmland (in terms of agricultural rent per acre). Attributes associated with and oil or gas lease were quite different than those for a wind lease; only share-based agricultural leases were a significant predictor for both.

Some externalities associated with oil and gas development affect all farms in an area, not just those that receive energy lease or royalty income. This is relevant to our work insofar as landowners' decisions regarding energy development are influenced by how they expect nearby landowners to behave. In some cases, farmers have reported feeling pressure to sign energy leases due to an expectation that they will need to deal with negative impacts from area energy development regardless of whether they choose to participate (Malin, 2014; Malin and DeMaster, 2016).

Using propensity score matching, Hoy et al. (2018) found evidence that gas development in the Marcellus Shale encouraged consolidation in the agricultural sector. In gas-producing counties, median farm size rose and the number of small farms fell relative to non-shale counties. Xiarchos (2017) also found a correlation between drilling intensity and a county having fewer, larger farms.

In areas of intense oil and gas production, farmers may compete with those industries for water, transportation, and labor. Despite efficiency improvements by drilling companies (Rodriguez and Soeder, 2015), hydraulic fracturing is usually a water-intensive process. Depending on the shale play, the typical unconventional gas well consumes from 1.5 million liters (California's Niobrara formation) to 23.8 million liters (Oklahoma's Woodford formation) of water (Kondash and Vengosh, 2015). While water useage by the shale oil/gas industry is not particularly large by national or state standards[2], it can significantly strain local resources. In a report for Ceres, Freyman (2014) notes that almost 39% of hydraulically fractured wells drilled since 2011 are in counties under "extremely high" water stress (more than 80% of available water being used). Farah (2017) found strong evidence that consumption of water for hydraulic fracturing in Alberta decreased yield for irrigated crops nearby. Farmers also compete with oil and gas companies for water in the United States, notably in Oklahoma and Texas (Cooley and Donnelly, 2012; Hitaj et al., 2014). While some farmers benefit by selling groundwater to energy companies, there is no effective mechanism to ensure that groundwater users are proportionately compensated (Allen, 2012). Transportation constraints in some shale plays have "shut in" some agricultural production, leading to lower commodity prices for area farmers. In 2014, a bumper crop combined with high demands for rail transport from oil producers led to serious transportation problems for farmers in the northern plains and upper Midwest (Prater, 2014). In North Dakota, the hardest-hit state, farmers lost between $66.6 and $162 million (Olson, 2014). Farms in energy-producing areas may need to pay higher prices for labor. Several studies suggest that growth in oil and gas production drives up an area's overall wage level, both through energy companies competing with other employers for local workers (Weber and Key, 2014; Deede, 2014) and by non-local workers increasing demand for housing and services (Muehlenbachs et al., 2015).

[2]For instance, it constitutes less than 2.5% of total water useage for mining in the United States and barely 0.1% of the water used for irrigation (Donnelly and Cooley, 2015).

Finally, farmers are not immune to the broader socioeconomic changes, both positive and negative, that arrive with energy development in their communities. A rich sociological literature deals with the social benefits and risks of rapid energy development. The shale gas revolution, in particular, prompted notable works by Brasier et al. (2011, 2015), Jacquet (2014), Ladd (2013), Perry (2012), and many others. It is difficult to generalize about the social impacts of an energy boom, both because those impacts vary from one community to the next and because the perceptions of change vary dramatically within communities. For some residents, an energy boom may bring improved government services, greater local educational and professional opportunities, and a sense of local identity and pride. Others in the same community may struggle to adjust to a larger and more transient population, greater income inequality, and changing work patterns. Illustrating this divide, research in Pennsylvania by Jacquet (2012) suggests that landowners' attitudes toward shale gas drilling vary dramatically depending on whether they directly benefit. Roughly 60% of landowners receiving lease and royalty income believe that drilling has made their community "better" or "much better"; the same percentage of landowners receiving no income from drilling believe it makes their community "worse" or "much worse"[3]. Most of these intangible costs and benefits fall beyond the scope of this thesis. Nevertheless, these and similar factors may influence both the willingness of farmers to lease land for energy development and participating farmers' plans for the future.

[3]This study also considered landowner attitudes toward wind power development. Landowners receiving royalty income from wind turbines were more likely to see a positive community impact, but landowners receiving no income from wind turbines were no more likely to have negative perceptions of wind development.

2.3 Income smoothing

The relatively consistent revenue stream from energy leases may act as a hedge against volatile crop prices and unpredictable weather. A 2013 study found a positive correlation between agricultural price volatility and farmers' willingness to lease land for solar development (Gazheli and Di Corato, 2013). The predictability of payments from this type of energy lease is also important. Farm households tend to treat outside income from variable sources (e.g. net farm income, insurance payments) differently than equivalent, but more predictable payments (e.g. decoupled support payments, off-farm salary income). Farmers are more willing to reinvest proceeds from the latter to increase production or productivity, rather than saving or consuming. Data from energy leases suggest that farm households perceive such lease income to be "moderately stable": it is less likely to be consumed (and more likely to be invested) than traditionally predictable payment sources, but more likely to be consumed than variable sources like net farm income (Weber et al., 2013). These hypotheses are reinforced by qualitative studies, like those of Malin and DeMaster (2016), reporting that the reliability of lease income is frequently cited as an important factor for farmers who have chosen to participate.

In this context, it is important to note that different kinds of energy leases have varying potential for income smoothing. Fossil fuel leases can produce a windfall during extraction, but the period of production is comparatively brief. Production of oil and gas drops even more quickly in wells drilled with hydraulic fracturing than in "conventional" wells. A study by King (2014) found that, without re-fracking, average production dropped by 70% over the first year. Wind or solar leases, in contrast, often last more than 20 years

(Farm Bureau New York, 2016; NY-SUN, 2016). These differences may affect the extent to which farmers reinvest lease income.

2.4 Credit-constrained farms

There is strong evidence of credit constraints for certain types of farmers, particularly newer farmers (Hartarska and Nadolnyak, 2012) or those with higher debt levels (Bierlen and Featherstone, 1998), that negatively impact farm productivity. Using propensity score matching (average treatment effect on the treated), Briggeman et. al studied the effects of credit constraints on U.S. sole-proprietorship farms and non-farm businesses (Briggeman et al., 2009). While credit constraints led to minor impacts on overall agricultural output, approximately 10.5% of U.S. farms lack sufficient access to credit. Credit constraints are a major issue for farm households affected. The value of a credit-constrained farm's production was almost $40,000 less than would otherwise be expected.

When banks and other financial institutions are unwilling to extend credit, farmers may look for other income derived from their farmland income to finance agricultural investment. Duke et al. (2016) found evidence that unprofitable (often credit-constrained) farmers are more likely than profitable farmers to reinvest conservation easement payments into their farms. The authors hypothesized that liquidity from conservation easement programs corrected a credit-market failure preventing some farmers from operating efficiently.

Interestingly, farm operators treat off-farm income (e.g., a household member's salary from a job "in town") differently than non-farming income that is nonetheless derived from farmland (e.g., conservation easement payments). Gedikoglu and McCann (2007) found that farm households used off-farm income to compensate for the unpredictability and variability of farming income. Harris et al. (2010) reported that farm households with off-farm income were less likely to invest in the farm. If a household with off-farm income did decide to invest in the farm, the presence of off-farm income did not increase the size of that investment. A study by Whitaker (2009) found that farm households had dramatically different short-term propensities to consume income from different sources, likely due to their perceived volatility. Households' marginal propensity to consume farm production income or unpredictable government income (loan deficiency payments and marketing loan gains) was just one-tenth that of off-farm income. Off-farm income, in turn, was less than half as likely to be consumed as decoupled subsidy payments, which are quite stable from year to year.

CHAPTER 3

DATA SOURCES

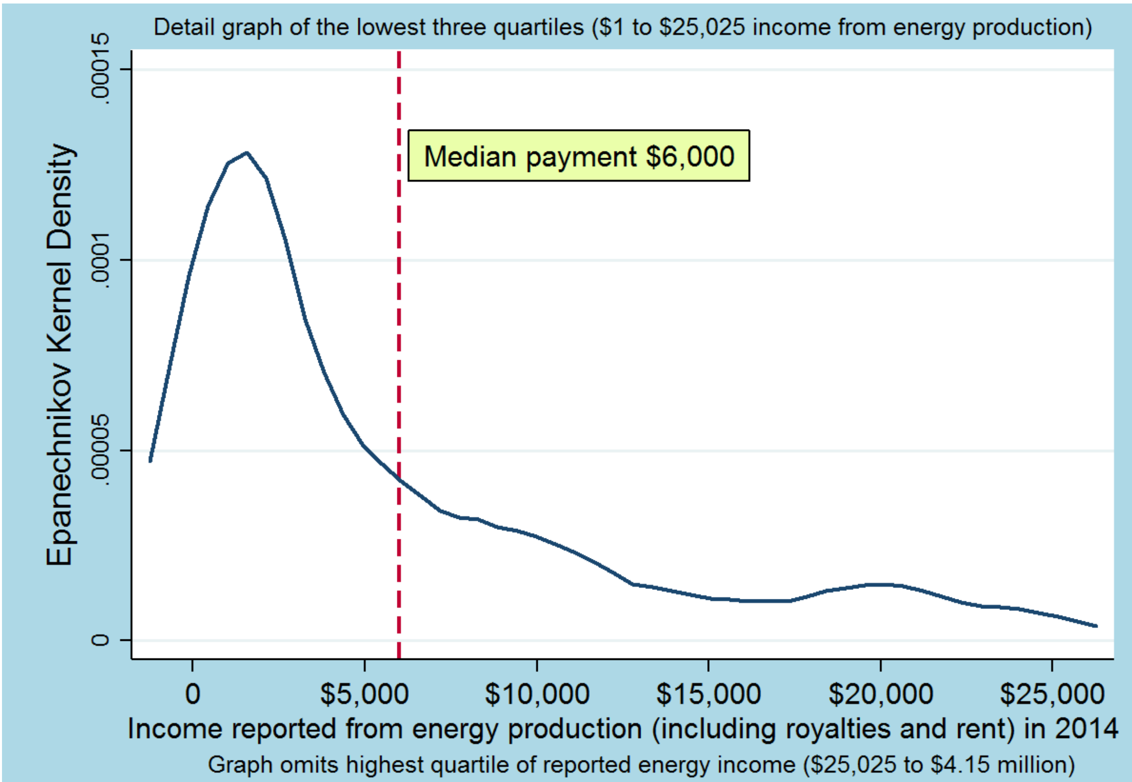
The principal source of data for this study is the 2014 TOTAL survey, conducted by the USDA National Agricultural Statistics Service (NASS) in collaboration with the USDA Economic Research Service (ERS). TOTAL collected detailed financial and land management information from 29,733 farmland owner-operators in the continental United States[1]. This study uses farm-level data, with location specified down to the county level. Including those derived by ERS, the data set includes more than 1,500 variables. It the first national survey of its type since the 1999 Agricultural Economics and Land Ownership Survey (AELOS), though TOTAL and AELOS results are not directly comparable due to differences in methodology (National Agricultural Statistics Service, 2015).

We based the binary treatment variables used for propensity score matching on questions 555, 7020, and 7026 from the TOTAL questionnaire. These questions, respectively, asked respondents to report income from "royalties or leases associated with energy production (e.g. natural gas, oil, and wind turbines)"; acres of owned land with the oil and gas rights leased out; and acres of owned land with other rights leased out. "Treated" farms were all those reporting income from the relevant source.

Of the 29,733 farm businesses in the TOTAL sample, 1,550 reported receiving income from energy production. A few farms reported very large payments (up to $4.15 million). However, the median payment was just $6,000.

[1]The TOTAL survey does not cover Alaska, Hawaii, or U.S. territories.

Figure 3.1: **Income from energy production, participating farms**



TOTAL is not a representative sample of U.S. farms, and reweighting is necessary to extend any conclusions from the sample to U.S. farms more broadly. ERS collected larger samples in the 25 states with the highest agricultural cash receipts. The likelihood of a given farm being in the TOTAL sample also increased based on its USDA-calculated farm value of sales.

3.1 County socioeconomic characteristics

While the TOTAL data set includes a great deal of detail about the farm businesses surveyed, it does not always include relevant socioeconomic information about those farms' surroundings. These gaps are important, since decisions about development of farmland must take into account many local factors. For example, one might expect energy development to face fewer obstacles in counties with lower population density, lower average incomes, or a more conservative population. We incorporated county-level census data to account for these and other local conditions.

Table 3.1: **Characteristics of farms in the TOTAL sample vs. all U.S. farms**

Mean per operation:	**TOTAL**	**All U.S. farms**[1]
Acres operated	946 acres	434 acres
Operator age	54.4 years	58.3 years
Net farm income	$161,821	$43,750
Value of farm equipment	$277,705	$115,706

(1) Summary per-operation statistics, 2012 Census of Agriculture

3.2 Energy production, transmission, and consumption

Unsurprisingly, the energy leases reported in TOTAL are geographically concentrated in areas with accessible energy resources. To account for variation in resource endowments[2], we incorporated county- and state-level data on crude oil, natural gas, wind electricity, and solar electricity production. This also allows us to correct for legal and regulatory

[2]TOTAL does include a question asking respondents about the value of mineral or other rights owned by the farm business. We opted not to use this variable, as it seems unlikely that landowners who have not sold, leased, or surveyed their mineral or other rights would have an accurate estimate of this value.

differences between jurisdictions (e.g., New York's ban on hydraulic fracturing) that make energy development more or less likely.

Oil and gas production

We use Energy Information Administration (EIA) data on production of crude oil and natural gas. At the county level, 2011 oil and gas production figures are the most recent available. The model also reflects whether county production is rising or falling significantly, based on the production volume change between 2000 and 2011. Since 2011 data might not capture the surge in production from unconventional sources, the model also uses the EIA's 2014 state-level production figures for oil and gas at the state level, adjusted for state area. The EIA also publishes maps of known oil- or gas-bearing shale formations; we use this data to estimate the likelihood that a given farm is located in a shale play.

Renewable energy potential and production

This study uses data from the National Renewable Energy Laboratory (NREL) Open PV project to estimate the cumulative capacity of solar power installed in counties through the end of 2014, complemented by EIA data on actual state-level net generation from solar. We drew on hourly average solar irradiation estimates by Perez et al. (2002) as a proxy for solar potential.

The American Wind Energy Association (AWEA) database on large wind projects is our source for estimated county wind generating capacity. We also relied on NREL's data

Table 3.2: **Sources of energy-related data**

American Wind Energy Association (AWEA)	
County wind generating capacity (2014)	
Energy Information Administration (EIA)	
County oil and gas production (2011)	County decline or growth of production 2001-11
State oil/gas production per square mile (2014)	Shale formation boundaries
State wind and solar net generation (2014)	State average retail electricity prices (2014)
State average retail natural gas prices (2014)	
National Renewable Energy Laboratory (NREL)	
Estimated wind power potential (1986)	County solar generating capacity (2014)
Oak Ridge National Laboratory	
Transmission infrastructure density	
Perez et al. (2002)	
Estimated hourly average solar irradiation	

to estimate wind resource endowment by county (Elliott et al., 1986; U.S. Department of Energy, 2015). NREL uses a 7-point scale for wind power potential at various heights; this study uses estimates for on-shore wind at 50 meters.

3.3 Transmission infrastructure density

Proximity to transmission infrastructure has a major impact on the cost of large-scale wind and solar development. Using Department of Homeland Security (DHS) data on the approximate location of high-voltage transmission lines, we generated a rough measure of electrical infrastructure density by calculating the length of lines in each county and adjusting for area (Oak Ridge National Laboratory, 2017).

3.4 Electricity and natural gas retail prices

In addition, we used EIA data on average state electricity prices and residential natural gas prices in 2014 as the basis for covariates in the propensity score algorithm. As noted above, Beckman and Xiarchos (2013) found a strong link between electricity prices and the propensity of farmers to adopt renewable energy technologies. Since free or discounted natural gas is sometimes part of a drilling lease (particularly for smaller, shallower wells) (Weidner, 2015), it seems reasonable to believe that high natural gas prices would make landowners more willing to lease land for gas drilling.

3.5 Other data sources

Finally, we incorporated county-level data on political beliefs and internet access. Previous research by Beckman and Xiarchos (2013), Borchers et al. (2014), and Xiarchos and Lazarus (2013) found these characteristics to be important predictors of wind and solar power adoption at the farm level[3]. We used counties' results in the 2016 presidential election, as compiled by McGovern (2016), as a proxy for an area's liberalism or conservatism. The Federal Communications Commission reports county-level data on fixed Internet connections twice annually. This study uses data on residential connections of at least 200 kilobytes per second per 1,000 county households as of December 31, 2014

[3] The TOTAL survey did not ask respondents about their political beliefs or their access to the internet.

(Federal Communications Commission, 2016).

CHAPTER 4

THEORETICAL AND ANALYTICAL FRAMEWORK

To guide our empirical work, we adapted theoretical models for (1) an owner-operator's decision to participate (or not) in energy development, (2) the impact of energy production income on farm income and spending, and (3) farm credit constraints.

4.1 Theoretical model of energy lease participation

Following Borchers et al. (2014), we hypothesize that the observed outcome of a farm reporting energy production income (a binary outcome that we will call *Lease*) is generated by an unobservable variable *Lease**. *Lease** represents the owner-operator's net expected benefits of leasing oil, gas, wind, or solar development rights. *Lease** will be positive if the expected value from energy development (lease payments, royalties, and any other benefits expected from a potential developer, assumed to be ≥ 0) exceed the expected tangible and intangible value from alternative uses of that land and any disamenities from energy development[1].

This study also assumes that the owner-operator's expected benefits and costs of energy leasing are a function of characteristics of the operating household (e.g., age and assets), farm operations (e.g., acres operated and value of production), and its physical and human geography (e.g., energy resources and socioeconomic surroundings). In addition, we allow for correlation between farms in the same state. This reflects variation in

[1]Some owner-operators in the TOTAL sample may receive income from energy production despite not consenting to energy development. Shared oil and gas resources, for instance, may be developed over the objection of a minority of rights-holders (often known as "forced pooling").

policies and regulation, not otherwise reflected in observed farm and area characteristics, that nevertheless can impact likelihood of energy development (Xiarchos and Lazarus, 2013; Borchers et al., 2014). Individual states have a great deal of leeway to decide how to permit, regulate, and tax energy production. In particular, many states impose restrictions on developing farmland that make energy production more difficult or expensive (Ifft et al., 2018).

Letting X_{ij} represent a vector of those independent variables for owner-operator i in jurisdiction j, the net expected benefits are generated by the following function. Both the farm-level and state-level random error terms (ϵ_i and μ_j, respectively) are assumed to have a normal distribution.

$$Lease_{ij}* = X_{ij}\beta + \epsilon_i + \mu_j \tag{4.1}$$

The relationship between $Lease_{ij}$* and the observed outcome is:

$$Lease_{ij} = \begin{cases} 1, & \text{if } Lease_{ij}* > 0 \\ 0, & \text{otherwise} \end{cases} \tag{4.2}$$

In this model, the probability that a given farm will report energy production income is:

$$P(Lease_{ij} = 1) = P(X_{ij}\beta + \epsilon_i + \mu_j > 0) \tag{4.3}$$

4.2 Empirical model: logistic regression

We used multiple logistic regressions to identify factors that influence participation or non-participation in energy leasing. Our final model handily satisfies the assumptions of logistic regression. A series of diagnostic tests, detailed below, suggest minimal multi-collinearity, linearity of independent variables and log odds, and high goodness of fit.

We estimate the log odds of farm i in state j having income from energy production with logistic regression, using covariates (x_1,x_2, etc.) that prior research suggest may play a role in leasing decisions. As noted above, standard errors are clustered by state to reflect variation in policies and regulation that are not fully explained by our covariates. The resulting functional form is:

$$\begin{aligned} Lease_{ij} &= ln(\frac{P(y_{ij} = 1}{1-(P(y_{ij} = 1)}) \\ &= \beta_0 + (\beta_1 \times x_{1ij}) + (\beta_2 \times x_{2ij}) + ... + (\beta_m \times x_{mij}) + \epsilon_i + \mu_j \end{aligned} \tag{4.4}$$

Results reported in section 5 reflect TOTAL-supplied sample weights to compensate for known differences between the sampled population and the actual population of U.S. farms.

4.2.1 Dependent variable and alternative specifications

Base specification

The dependent variable in the base specification simply reflects whether a farm reported *any* income from energy production in 2014. 1,550 of the 29,733 owner-operators surveyed for TOTAL reported some energy income.

Alternative energy income variables

Since the median energy production payment to participating farms is relatively small (see Figure 3.1), it is important to consider whether the results of the base specification hold if we define a more selective treatment group. We report results for two variations on the base variation specification that focus on energy payments that are "substantial" in either relative or absolute terms. A farm operator may weigh the costs and benefits of an energy lease based on the size of expected payments relative to net farm income. As such, our first variation limits the treatment group to farms that received at least 50% of net farm income from energy production income in 2014 (679 farms in the

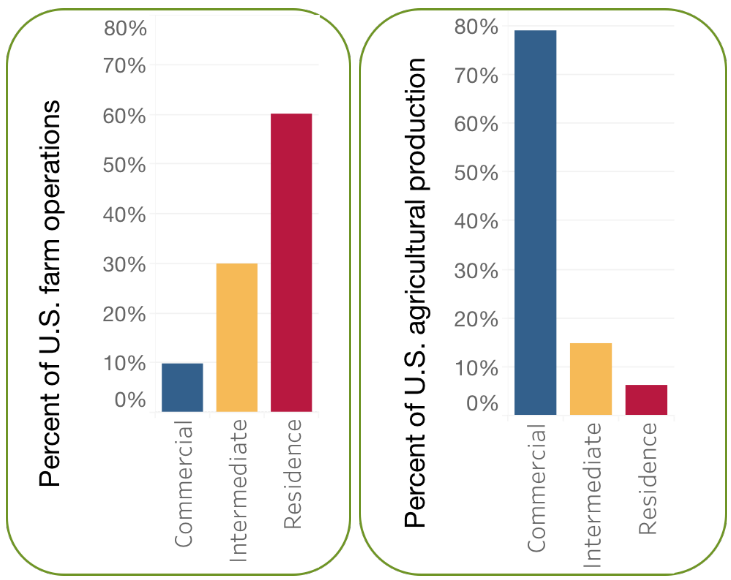
Table 4.1: **Number of treatment and control observations, by specification**

	Treatment group	Control group
ANY energy production income	1,550	28,183
Energy income ≥ 50% of net farm income	679	29,054
Energy income ≥ $10,000	616	29,117

sample). It may also make sense to differentiate between smaller and larger energy development deals. The dependent variable for the second variable is whether a farm received at least $10,000 (616 farms).

Alternative population: intermediate- and commercial-scale farms

Figure 4.1: **U.S. farms and agricultural production, by USDA farm type**



Data from Hoppe and MacDonald (2013)

Some 60% of U.S. farms are classified as "residence" operations by the USDA: farms with gross income below $350,000 and an operator who does not consider farming to be his/her primary occupation (Hoppe and MacDonald, 2013). However, the vast majority of U.S. agricultural production is by "intermediate" or "commercial" farms. Intermediate farms also have gross income below $350,000, but the principal operator considers farming to be his or her primary occupation. Commercial farms either have gross sales greater than $350,000 or are nonfamily operations.

All U.S. farms are in the population of interest for the above specifications. After weighting, the results predominantly reflect expectations for residence farms. However, given larger farms' comparative importance in U.S. agricultural output, it is important to consider whether they respond in the same way to potential energy income. To address this issue, we repeated the three logistic regressions described above using only the 18,958 farms in the TOTAL sample that were classified as intermediate- or commercial-type operations by the USDA.

Table 4.2: **Professional farm variations: number of treatment and control observations**

	Treatment group	Control group
ANY energy production income	1,128	17,830
Energy income ≥ 50% of net farm income	437	18,521
Energy income ≥ $10,000	473	18,485

Oil and gas vs. other leases

Finally, we compare the characteristics of farms reporting oil and gas leases to those leasing other types of property rights to shed light on which, if any, attributes identified in our study are associated specifically with energy leases as opposed to leases

Table 4.3: **Oil and gas vs. other leases: number of treatment and control observations**

	Treatment group	Control group
Leased oil or gas rights for some acre(s) owned	1,400	28,333
Leased other rights for some acre(s) owned	531	29,202

106 observations are in both treatment groups.

more broadly.

The TOTAL survey asks owner-operators if (a) oil and gas rights or (b) other rights have been leased on any land owned by the farm business. We reduce these to simple binomial outcomes comparable to those used above. These outcome variables reflect only the presence or absence of a lease, not whether it has been developed or is currently generating income. Almost half (49.5%) of farms reporting an oil and gas lease did not receive any energy production income in 2014[2]. The oil and gas treatment group would not include farms that have *sold* land for hydrocarbon drilling or farmers affected by oil or gas development on farmland that they rent from another landowner.

4.2.2 Selecting covariates

We identified potential covariates for based on prior research of important considerations for farmers considering leasing land and economic theory. Working from this inclusive list, we developed a relatively parsimonious logistic regression model through an iterative process of (1) testing for multicollinearity, (2) identifying potentially redundant variables, and (3) comparing the reduced and full models. Covariates used in the final specifications of the predictive logistic model are described in the tables below.

A series of diagnostic tests shows no obvious violations of the assumptions underlying logistic regression. A variance inflation factor (VIF) test indicates relatively low multicollinearity. The mean VIF for covariates in our final predictive model is 1.65; the

[2]See Appendix A for a tabulation of the overlap between farms that have leased oil and gas rights, those that have leased other rights, and those that reported receiving energy production income.

Table 4.4: **Predictive logit model: farm business variables**

Acres owned	Total acres of farmland owned (not necessarily operated)
Conservation programs	Income received from the Conservation Reserve Program (CRP), Conservation Reserve Enhancement Program (CREP), Environmental Quality Incentives Program (EQIP), Conservation Security Program (CSP), and the Conservation Stewardship Program (CStP)
Contract	Farm produced one or more commodity under a production or marketing contract
Debt to asset ratio	Ratio of total farm debt to total farm assets
Farm debts (total)	Balance of loans outstanding at the end of 2014
Fixed costs	Overhead expenses that do not vary with production
Land rented *from* others	Percent of land operated that is rented from another landowner
Production specialty	More than 50% of farm revenue is from livestock and animal products; grains and oilseeds; fruits and vegetables; or none of these.
Value of farm production	Gross farm revenue

Table 4.5: **Predictive logit model: farm operator and household variables**

Age	Principal operator's age on December 31, 2014
Dependence on farm income	Ratio of net farm to total household income
Education	Highest level of education achieved by principal operator or spouse
Farming experience	Years that the principal operator has run *any* farm
Female	Principal operator identifies as a woman
Hours worked annually	Hours worked on farm by principal operator, per year (1000s)
Non-farm assets	Household assets not associated with farming
Non-farm debt (total)	Principal on loans taken out for exclusively non-farm purposes
Off-farm income	Household income from activities not associated with the farm business or farm assets
Residence	Principal operator lives on-farm
Retirement plans	Whether the principal operator plans to retire from farming in the next 5 years
Risk tolerance	Self-reported willingness to take risks, on a 10-point scale

Table 4.6: **Predictive logit model: energy resource variables**

County: crude oil production	Total crude oil production in 2011
County: gas production	Total natural gas production in 2011
County: production *decline*	Value of oil and gas production fell by $10 million or more between 2000 and 2011
County: production *increase*	Value of oil and gas production rose by $10 million or more between 2000 and 2011
County: relative solar potential	Average annual solar irradiance in the given county, compared to other U.S. counties (expressed as a percentile)
County: wind potential	Best wind resource quality in the given county (50 meters above surface), as assessed by the U.S. Department of Energy
State: electricity prices	Average residential retail electricity price in 2014
State: crude oil production	2014 crude oil production, adjusted for state area
State: gas production	2014 natural gas production, adjusted for state area
State: wind production	Net generation from wind in 2014, adjusted for state area

Table 4.7: **Predictive logit model: socioeconomic surroundings**

County: household income	Income of median county household, 2010
County: internet access	Internet connections per 1000 households
County: partisan lean	Percent of county votes cast for Hilary Clinton in 2016 election
County: population density	Average county population per square mile, 2010
County: racial diversity	Percent of county self-identifying as white, 2010
State: electricity prices	Average retail electricity price (all sectors) in county in 2014
State: natural gas prices	Average retail natural gas price (all sectors) in county in 2014

highest individual covariate's VIF is 3.10. A Hosmer and Lemeshow goodness-of-fit test (10 groups) produced a p-value of .6481, suggesting that our logistic model fits the data quite well (Hosmer and Lemesbow, 1980). A link test for model specification, following the method laid out in Pregibon (1980), is also encouraging, showing no evidence of specification error.

Bidirectional (cyclic) causation is a potential problem with our data set, but can be mitigated by using ordinal or binary rather than continuous variables. Many of the variables collected by the ARMS survey both influence and are influenced by energy lease participation. For example, a given farmer's household income would likely influence his or her interest in signing an energy lease; energy lease participation also affects household income. Thus, a continuous household income covariate could introduce bias. This risk can, however, be greatly reduced by using a categorical household income covariate separating farms into quartiles based on household income. Revenue from an energy lease can make a meaningful difference in a household budget, but it is unlikely to shift a household from one income quartile to another. As noted in chapter 3, the median farm reporting energy production income received $6,000 in 2014. In relative terms, the median farm received 3.1% of its gross income from energy production. The median payment in the intermediate- and commercial-type farm sample was only slightly higher: $7,000.

4.2.3 Compensating for missing values of covariates

Only four of the relevant TOTAL covariates have missing data. However, the data is not missing completely at random in relation to key farm characteristics. The table below illustrates this point by showing non-response rates for the three relevant covariates with missing data, grouped by ERS farm typology. The simplest response to missing data, dropping incomplete observations, is not tenable in these conditions. Excluding observations with missing data would reduce our model's power and could introduce bias (Mitra and Reiter, 2011).

We also decided against imputing values for missing data, as that would require the dubious assumption that missingness (m) is independent of the relevant variable's value conditional upon a vector of known independent variables (Sterne et al., 2009): $f(Y_x|X, m = 0) = f(Y_x|X, m = 1)$. Rather, the relationship between between Y_x and X may vary depending on whether Y_x is observed. The nonresponding group may have some otherwise unobserved common characteristic. For example,

Table 4.8: **Percent of observations missing data, by farm type**

	Residence farms	Intermediate farms	Commercial farms
Years of experience[1]	10.1%	14.6%	8.1%
Retirement plans[2]	3.9%	10.0%	4.6%
Risk tolerance[3]	3.1%	10.7%	4.7%
Off-farm income[4]	0%	0%	5.8%

Text in TOTAL questionnaire:
(1) In what year did the operator begin to operate ANY farm?
(2) Do you (the principal operator) plan to retire from farm work within the next 5 years?
(3) Are you generally a person willing to take risks or do you try to avoid taking risks?
(4) [What was] the total income the household, the principal operator, and spouse received in 2014 from all off-farm wages, salaries, and tips before taxes and withholdings?

farmers considering retirement might skip the TOTAL question asking about retirement plans (see above) because it does not allow for uncertainty.

A more conservative assumption is that the data is missing not at random. Under this assumption, we added a “did not respond” category for each of the four covariates specified.

4.3 Theoretical model: impacts of energy production income on net farm income and capital investment

In the TOTAL survey, energy production income on land owned by a farm business is considered to be part of that farm’s net income. As such, it may seem self-evident that farms with energy production income would have measurably higher net farm income. If owner-operators are free to refuse unfavorable contracts, it follows that farmers who allow energy development expect the benefits to outweigh the costs. Previous studies, notably Weber et al. (2013) and Hitaj et al. (2018), have even quantified the positive impacts of oil and gas development on farm household income and wealth.

However, the relationship between energy production income and net farm income may be more ambiguous. The positive impact on wealth observed for farm households with an energy lease is largely attributable to increased land values rather than to energy payments *per se* (Weber et al., 2013; Weber and Hitaj, 2015; Xiarchos, 2017). Focusing on the farm operation’s balance sheet, the positive impact of energy income may be counteracted if energy production leads to a decrease in the host farm’s agricultural output (e.g., by reducing the acreage available for farming, decreasing productivity of surrounding land, or encouraging household members to devote less time to farming) or limits the owner-operator's access to other sources of on-farm income (e.g., agritourism or non-energy development). Due to these and related effects, the impact of energy development on a farm's net income may be rather less than the sum of royalties and other energy payments received.

Even if farms with energy leases have higher net farm income, operators would not necessarily reinvest that income in their farm business. Previous research by Gazheli and Di Corato (2013) suggests that farmers smooth their spending over time, consistent with a traditional life-cycle model (Friedman, 1957; Ando and Modigliani, 1963). In a traditional life-cycle model, the effect of energy production income on capital spending would probably not be observable. Energy leases make up a very small part of annual household income for most participating farms, let alone expected lifetime income. However, there is also evidence that farmers' marginal propensity to spend income differs depending on the perceived predictability of the income stream. Farm operators likely practice a degree of context-dependent "mental accounting" as used in behavioral economic models pioneered by Thaler (1985) and Kahneman and Tversky (2013). This complicates the life-cycle model. Energy production income seems to be viewed as relatively predictable and, thus, farm households are more likely to spend income from this source (see Weber et al. (2013) and Malin and DeMaster (2016)).

Thus, this study uses a hybrid theoretical model of farm consumption developed by Carriker et al. (1993) and subsequently adapted by Whitaker (2009) and Weber et al.

(2013). While it is grounded in a life-cycle framework, the model developed by Carriker et al. uses a system of consumption functions to allow for varying marginal propensity to consume different streams of income. In the equations below, for a household with k streams of income, Y represents disposable income, C is income consumed (which, here, would include capital spending), W is wealth, and t refers to time. The household's minimum possible consumption (regardless of income) is the sum of the β_0 terms. The λ values, which sum to 1 across the system of equations, reflect the proportion of household consumption from the given income source.

$$\begin{aligned}
\lambda_1 C_t &= \beta_{01} + \beta_{11} Y_t + \beta_{21} C_{t-1} + \beta_{31} W_t \\
\lambda_2 C_t &= \beta_{02} + \beta_{12} Y_t + \beta_{22} C_{t-1} + \beta_{32} W_t \\
&\dots \\
\lambda_k C_t &= \beta_{0k} + \beta_{1k} Y_t + \beta_{2k} C_{t-1} + \beta_{3k} W_t
\end{aligned} \tag{4.5}$$

These equations may be combined to produce an estimable function, in which the β_1 term represents the short-term marginal propensity to consume for the income source of interest (s). For this study, of course, we are only concerned with propensity to consume energy production income.

$$\begin{aligned}
C_t &= \sum_{s-1} \lambda_s C_t \\
&= \sum_{s-1} (\beta_{0s} + \beta_{1s} Y_s + \beta_{2s} \lambda_s C_{t-1} + \beta_{3s} W_t) \\
&= \sum_{s-1} \beta_{0s} + \sum_{s-1} \beta_{1s} Y_{st} + \sum_{s-1} \beta_{2s} \lambda_s C_{t-1} + \sum_{s-1} \beta_{3s} W_{st}
\end{aligned} \tag{4.6}$$

Finally, Carriker et al. note that long-term marginal propensity to consume income from a given income stream may be inferred from the above function, accounting for the rate of consumption growth. Here, g is the annual average consumption growth rate. The average ratio of wealth to income from source k is given by $\bar{\omega}$.

$$MPC_s = \frac{\beta_1 + \sum\limits_{s-1} \beta_{3s} \frac{\partial W_t}{\partial Y_{st}}}{1 - \frac{\sum\limits_{s-1} \beta_{2s}}{(1+g)}} \approx \frac{\beta_{1s} + \sum\limits_{s-1} \beta_{3s} \bar{\omega}}{1 - \frac{\sum\limits_{s-1} \beta_{2s}}{(1+g)}} \tag{4.7}$$

If farmers view energy production income as stable relative to other farm revenue streams, as suggested by Gazheli and Di Corato (2013), Weber et al. (2013), and Malin and DeMaster (2016), we would expect farms to have a higher marginal propensity to consume energy production income than other farm income, including income from agricultural production or other activities displaced by energy development. Under these conditions, the Carriker et al. model suggests that farms with energy production income would be more likely to invest in capital goods. Among farms that made some capital investment in 2014, the model suggests that, overall, farms with energy income would make larger investments.

4.4 Theoretical model: impacts of energy income on credit constraints

Another financial outcome of interest is credit constraints. Our hypothesis is that farms with energy production income are less likely to report such constraints.

Given that there are several mechanisms by which energy production may influence credit constraints, this study takes a relatively inclusive approach to defining which farms are credit constrained. TOTAL differentiates between farm respondents who were turned down for a loan, those who were approved for a smaller loan than requested, and those who wanted a loan but did not apply because they expected to be turned down. This study, which uses credit constraints as an outcome variable, considers farmers reporting *any* of those circumstances to be similarly credit constrained (1,027 farms in the TOTAL sample). This aggregation requires us to rely on farmers' self-reported reasons for not seeking credit. It is supported by research by Jappelli (1990), Crook (1996), and others suggesting that would-be borrowers discouraged from seeking credit act similarly to those actually refused credit.

However, the very existence of credit constraints for farmers requires some explanation. In a perfect capital market, that Utopian vision described in Economics 101 textbooks, credit is governed by simple supply and demand. Interest rates are set through the costless negotiation of absolutely enforceable contracts between perfectly rational lenders and borrowers, both with full information. Nobody is denied credit; riskier borrowers are just subject to higher interest rates and collateral requirements. In practice, alas, lenders and borrowers must deal with with limited information, burdensome transaction costs, difficult contract enforcement, adverse selection effects, prejudice, and other credit market distortions. In this environment, lenders often employ credit rationing: rather than offering a higher-interest loan, lenders offer smaller loans than requested or refuse credit altogether to riskier (or structurally disadvantaged) borrowers (Jaffee and Russell, 1976; Jappelli, 1990; Stiglitz and Weiss, 1992). For a variety of reasons, lenders often behave differently toward financially-identical loan applicants; a borrower's financial characteristics do not perfectly predict access to credit.

Hartarska and Nadolnyak (2012), Bierlen and Featherstone (1998), and Briggeman et al. (2009) found strong evidence of credit constraints affecting U.S. farm households (see Section 2.4). We use the credit constraints model developed by Briggeman et al. (2009), which conceives of binding credit constraints as the result of asymmetry of information between lenders and would-be borrowers.

Briggeman et al. begin from the premise that economic actors (here, farm households) borrow to maximize utility (u) over time. This is consistent with neoclassical producer-consumer models for agricultural households (Singh et al., 1986; Bezuneh et al., 1988; Petrick, 2004). In this producer-consumer framework, utility is produced through a twice-differentiable, quasi-concave function of consumption (c) over time, given exogenous household characteristics (z^h). For simplicity, time may be divided into two periods, 0 and 1. In period 0, the household may use liquid (a) or borrowed funds (B) to purchase variable inputs (x) at price p in order to produce a quantity of economic goods (q). Production, revenue generation, repayment of borrowed funds with interest (r), and non-business activities (N) take place in period 1. Letting z^q represent all production inputs, the (concave) production function is $q = f(x; z^q)$. As laid out by Briggeman et al., this produces the following system of equations:

$$\max_{c_0>0, c_1>0, x>0, B\geq 0} u(c_0, c_1; z^h) \tag{4.8}$$

s.t.

$$a + B - c_0 - px = 0 \tag{4.9}$$

$$f(x; z^q) + N - c_1 - (1 + r)B = 0 \tag{4.10}$$

Equations (4.9) and (4.10) constrain the utility maximization function (4.8) by introducing budget constraints for periods 0 and 1, respectively. Next, Briggeman et al. introduce a credit constraint function (which may be binding or non-binding) produced by household and production characteristics:

$$\bar{B}(z^h, z^q) \geq B \tag{4.11}$$

Equation (4.11) assumes that, given exogenous interest rates, borrowers may use less credit than they would like because of information asymmetry between borrower and lender. With limited ability to identify "bad borrowers," it may be in lenders' interests to impose some form of credit rationing on their customers (Stiglitz and Weiss, 1981). Would-be borrowers, for their part, may overestimate the likelihood of being refused credit.

If the credit constraint is binding ($\bar{B} = B$), the optimal solution for equations (4.8)-(4.10) is:

$$\frac{\partial f(\cdot)}{\partial x} = p((1 + r) + \frac{\eta}{\lambda}) \tag{4.12}$$

The effect of the credit constraint is the addition of η and λ representing the Lagrangean multipliers produced by, respectively, the credit constraint in period 0 and the budget constraint in period 1. In the absence of a credit constraint, we need only inflate p by r to get the present-value opportunity cost. If, as is logical, the Lagrangean multipliers are positive, then Briggeman et al. conclude that a credit constrained household must, relative to an unconstrained household, have a higher present value opportunity cost, a lower optimal quantity of inputs purchased (x) and, therefore, lower production (q).

Adapting the above model for our study, we expect that energy production income relieves credit constraints for participating farmers in several ways. Most obviously, farmers can use lease income and royalties in lieu of loans to finance operations or improvements (an increase in a that, all else being equal, would diminish B). In addition, a farmer with an energy lease may be in a stronger position to obtain credit if the lease increases the value of farm assets that he/she can leverage (a change to z^h increasing $\bar{B}$). Finally, it is possible that energy lease income has a psychological effect: participating farmers may be more likely to apply for credit when needed if energy assets increase the perceived likelihood that their credit application will be approved (a change to z^h with a non-negative effect on $\bar{B}$). Under this framework, we hypothesize a that energy production income will decrease self-reported capital constraints.

4.5 Empirical model: propensity score matching

In experimental research, subjects are typically randomly assigned to treatment and control groups. This ensures that the treatment and control groups are statistically equivalent: identical in all respects other than the parameter of interest. In such circumstances, the observed average treatment effect (ATE) of an intervention is equivalent to the average treatment effect on the treated (ATT). Given a binary treatment variable t, this may be summarized as:

$$ATE = ATT = E(\Delta) = E(Y_{t=1} - Y_{t=0}) \tag{4.13}$$

In non-experimental studies, assignment of subjects to treatment and control groups is rarely truly random. In this study, for instance, there are systematic differences in the characteristics of farms that do and do not choose to host energy projects. A useful way to illustrate this point is to simply compare key characteristics of farms with and without an energy lease. Limiting the sample to farms in energy-producing counties or commercial-scale operations reduces the differences but does not eliminate them.

Clearly, the impact of energy development cannot be inferred by simply comparing outcomes for participating and non-participating farms; there is selection bias. Instead, estimating the ATT requires comparing the observed outcome for participating farms with its counterfactual: the outcome for those farms in the absence of an energy lease.

$$ATT = E(Y_{t=1}|t = 1) - E(Y_{t=0}|t = 1) \tag{4.14}$$

This creates a conundrum for the researcher, often called "the fundamental problem of causal inference": it is impossible to observe the outcome of treatment and non-treatment for any single subject. A common response to this problem is the assumption of unit homogeneity. That is, an individual outcome is a function of treatment and the uniform effects (even if unobserved) of that individual's characteristics (Holland, 1986). Under this assumption, an untreated subject is a valid counterfactual of a treated subject if the only relevant difference between the two is the treatment itself (Rubin, 1974). Matching techniques address the selection bias problem by pairing each treated research subject with one or more subjects from the comparison group with similar (relevant) pre-treatment characteristics. Matching becomes exponentially more difficult, however, as one considers

Table 4.9: **Mean characteristics of farms in TOTAL sample with and without an energy lease**

	All farms		*Energy counties*[1]		*Commercial farms*	
	lease	no lease	lease	no lease	lease	no lease
Acres operated	2130	881	2190	975	3940	1760
p-value	*(0.000)*		*(0.000)*		*(0.000)*	
Risk tolerance[2]	5.60	5.34	5.54	5.37	6.40	6.12
p-value	*(0.000)*		*(0.026)*		*(0.003)*	
% college grads[3]	33.0%	28.0%	32.9%	29.6%	35.2%	28.6%
p-value	*(0.000)*		*(0.014)*		*(0.001)*	
Hours worked/yr[4]	2220	2020	2200	2010	2840	2800
p-value	*(0.000)*		*(0.000)*		***(0.426)***	
Years experience[5]	34.0	29.5	34.0	29.2	33.9	30.3
p-value	*(0.000)*		*(0.000)*		*(0.000)*	

Notes: Three significant digits, two-sided p-value of difference in means in parentheses

(1) Farms located in counties with significant oil, gas, solar, or wind production

(2) Operator willingness to take risks (self-reported on a 0 to 10 scale)

(3) Percent of principal operators in specified group with a 4-year college degree

(4) Total hours worked on the farm by the principal operator

(5) Years that the principal has operated ANY farm

additional relevant characteristics. Richard Bellman's infamous "curse of dimensionality" (Bellman and Kalaba, 1959) makes direct matching a practical impossibility for all but the simplest economic models .

The crucial innovation of propensity score matching, first described in Rosenbaum and Rubin (1983), was to match subjects on the probability of a given subject being in the treatment group. The "propensity score" itself may be estimated from a vector of observed variables that predict participation or non-participation in the treatment or program of interest. Conditional on the propensity score, treatment assignment is strongly ignorable: subjects are equally likely to be in the treatment or comparison group. The ATT estimator is the mean difference in outcomes between treated and untreated subjects, weighted by the probability of those subjects being in the treatment group.

$$ATT_{PSM} = E_{P(X)|t=1}[E(Y_{t=1}|t = 1, P(X)) - E(Y_{t=0}|t = 0, P(X))] \tag{4.15}$$

Propensity score matching offers several compelling advantages over other non-experimental methods. If properly executed, the technique can balance treatment and control groups on a large number of covariates without sacrificing a large number of observations (Olmos and Govindasamy, 2015). It is not unusual for researchers to take hundreds of covariates into account when calculating propensity score (Garrido et al., 2014). Propensity score matching also has the advantage of reducing data, converting many fine measures to a single coarse measure of similarity (Rosenbaum and Rubin, 1983). If the goal is to calculate ATT, propensity score matching operates well when treatment is rare (Caliendo and Kopeinig, 2008). Overfitting does not introduce bias or inconsistency, as the model for propensity score estimation is intended to describe existing data rather than to generalize for other data (Sainani, 2012)[3]. Thus, a propensity score model may consider a large number of covariates compared to, for instance, a straightforward OLS regression.

Due to these advantages, propensity score matching and its variants have proved popular for a wide range of research questions. Agricultural economists have used propensity score matching to address subjects as diverse as the impact of agricultural technology adoption on poverty (Mendola, 2007), the effectiveness of easement purchases for farmland preservation (Liu and Lynch, 2011), and comparing the productivity and technical efficiency of organic and conventional dairy farms (Mayen et al., 2010)

However, propensity score matching also requires two key assumptions. First, propensity score matching depends upon common support: all subjects must have a probability of being part of the treatment group between 0 and 1 (Heinrich et al., 2010). Simply put, there is no basis for a comparison if a subject with particular characteristics is *never* or *always* treated. This is also known as the overlap condition (Caliendo and Kopeinig, 2008).

Second, propensity score matching requires selection on observables: the propensity score must reflect all characteristics relevant to determining treatment status, including those that simultaneously affect treatment status and outcomes[4]. Omitted variables can significantly distort propensity score matching models, as shown by Smith and Todd (2005),

[3] *Extraneous* covariates can increase the variance of propensity scores and reduce the region of common support (Caliendo and Kopeinig, 2008). This risk is reduced, though not eliminated, by our large sample size.

[4] In some papers, this is called unconfoundedness or the conditional independence assumption, referring to the fact that potential outcomes are independent of treatment assignment conditional upon the vector of observed covariates.

Agodini and Dynarski (2004), Heckman et al. (1998), among others. Problems frequently arise with data sets that contain few independent variables, few observations, independent variables compiled from multiple sources, or treatment and control groups that differ in geography, time, or data-gathering process (Smith and Todd, 2005). In contrast, the large, detailed ARMS data set used for this study is exceptionally well-suited to a "data-hungry" propensity score matching approach. A series of balancing tests (described in more detail below) confirms that, conditional upon the propensity score, farms operators in our study were equally likely to be in the treated or untreated group.

4.5.1 Selecting covariates

Our propensity score matching model used all of the covariates identified for the logistic regression model (see section 4.2.2), with some additions described in Table 4.10. As noted above, propensity score matching models are vulnerable to omitted variable bias (hence the selection on observables assumption), but are tolerant of overfitting. Extraneous variables do not introduce bias or inconsistency, though they can increase the variance of propensity scores and reduce the region of common support in smaller samples (Caliendo and Kopeinig, 2008). Here, again, the large TOTAL sample offers some protection.

That said, the selection on observables assumption is an important limitation of this model. Despite the large data set and encouraging results from model diagnostic tests (see below), there is always some risk that the model is missing a key driver of energy leasing. For example, we could not include covariates directly reflecting the beliefs and motivations of a given farm operator, the agricultural value of land leased for energy development, or

Table 4.10: **Covariates omitted from predictive model included for propensity score estimation**

ERS region	Location in one of nine ERS-designated production regions
Household net worth	Total assets of household members, farm and non-farm
Large-scale solar	County contained at least one megawatt-scale solar facility by end of 2014
Large-scale wind	County contained at least one MW of large-scale wind capacity by end of 2014
Metro county	Census-designated metro county
Non-metro recreation area	Non-metro county with significant recreation assets, designated by the U.S. Census
Plans to sell land	Operator plans to sell land within the next three years
Retired	Principal operator is currently retired
Shale county	Percent of host county located over an oil- or gas-bearing shale formation
Share-based rent	Percent of acres operated that is rented from another landowner solely in exchange for a share of production
State solar generation	Net generation from solar in 2014, adjusted for state area
Transfer to relative	Plan to sell or transfer farmland to a relative within the next five years
Transmission density	High-voltage transmission lines in host county per square mile, compared to other U.S. counties (expressed as a percentile)

the impact of relatively permissive or restrictive local governments. Each of these could impact an owner-operator's response to energy development opportunities in ways not fully captured by other covariates.

4.5.2 Propensity score estimation model

Logit, probit, and linear probability models are commonly used to estimate propensity scores with a binary treatment (here, whether a given farm reported receiving royalty or lease income from energy production in 2014). The functional form of the linear probability model is ill-suited to predicting a highly-skewed treatment variable (there are many more untreated than treated subjects) and that model also produces propensity scores outside of the logical bounds (0 to 1) (Smith, 1997). It may be rejected. Akaike's information criterion (AIC) suggests that the difference between logit (AIC value of 9365) and probit (AIC value of 9366) models is negligible; we opted for a logit estimation model.

For continuous covariates, we added fractional polynomials to the estimation model to compensate for nonlinear relationships. This portion of the model was based on a closed test procedure using $\alpha = 0.05$. A model incorporating fractional polynomials offers a significantly better fit to the data. The AIC value of the non-polynomial base specification is 9142; AIC for the model with polynomials is 8712.

4.5.3 Matching algorithm

Researchers have proposed many matching algorithms to compare treated and untreated subjects in propensity score matching models. Rosenbaum and Rubin (1983) used a "nearest neighbor" approach pairing each treated subject to the most similar untreated counterpart in the sample, without replacement. Later widely-used propensity score matching variants imposed calipers restricting nearest neighbor matching (Austin, 2011), compared each treated observation to all untreated observations with a propensity score within a given radius (Dehejia and Wahba, 2002), partitioned the region of common support into strata (Dehejia and Wahba, 1999), or used a kernel-weighted average of multiple untreated observations to construct a match for treated individuals (Heckman et al., 1997). None of these approaches consistently outperform the others (hence the survival of such diversity in matching algorithms); the best approach depends on the structure of underlying data. The results of different propensity score matching algorithms tend to converge as sample size increases and the average quality of matches improves (Caliendo and Kopeinig, 2008).

4.5.4 Balancing tests

To identify the best matching algorithm for this study, we used a series of balance tests on three promising matching algorithms: nearest neighbor (without replacement), radius matching[5], and Epanechnikov kernel weighting. Nearest neighbor with replacement, stratification and Gaussian kernel weighting were also tested and rejected. The tables below highlight results for ten covariates hypothesized to be important predictors of energy leasing.

Table 4.11 uses t-tests to compare mean values of covariates for farms that did and did not report income from an energy lease. The table shows two values for each covariate: the t-score[6] and the estimated percent bias for that covariate. For each test, the null hypothesis is that, controlling for the propensity score, there is no difference in means between the treated and untreated group. Results highlighted in red are statistically significant at the $\alpha = 0.05$ level, suggesting that the researcher may reject the null hypothesis in favor of an

[5]We used a radius equal to 20% of the propensity score standard deviation, following Rosenbaum and Rubin (1985).

[6]The t-score represents the difference between the covariate's mean value in the the treated and untreated groups in terms of standard errors. T-scores over 1.96 are statistically significant at the $\alpha = .05$ level. In other words, 5% of samples drawn from balanced groups should produce a t-score greater than 1.96

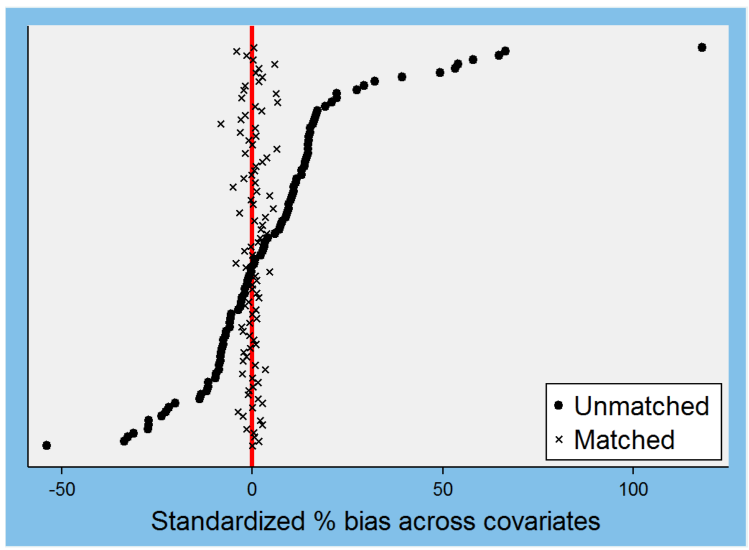
Table 4.11: **T-tests for equality of means: treated and untreated groups**

Selected covariates	Unmatched	Nearest Neighbor	Radius	Epanechnikov kernel
Acres owned	**-11.48**	0.6	-1.42	**-2.53**
	-37.5%	*1.3%*	*3.4%*	***-6.3%***
Debt-to-asset ratio	**2.46**	-0.48	-0.3	0.09
	6.9%	*-1.6%*	*-1.0%*	*0.3%*
Annual hours worked on farm by principal operator	**30.38**	-0.35	0.72	1.36
	61.5%	*-1.5%*	*3.1%*	*5.8%*
Percent of county located over an oil- or gas-bearing shale formation	**6.14**	-1.32	-0.18	0.26
	16.3%	*-4.8%*	*-0.6%*	*0.9%*
High off-farm income (highest quartile in sample)	**5.91**	1.25	1.03	1.19
	14.2%	*4.7%*	*3.9%*	*4.5%*
Located in an oil- or gas-producing county	**42.12**	0.23	1.11	2.85
	117.7%	*0.8%*	*3.7%*	*9.7%*
Percent of land operated that is rented from another landowner	**3.7**	-0.57	-0.59	-0.35
	10.1%	*-2.0%*	*-2.1%*	*-1.2%*
High-production farm (highest quartile in sample)	1.24	-1.09	-0.5	-0.26
	3.2%	*-4.0%*	*-1.8%*	*-0.9%*
Average solar irradiation in county (Percentile among all U.S. counties)	**3.64**	0.37	1.09	-1.2
	8.7%	*1.4%*	*-4.3%*	*-4.7%*
County contains "good" or better wind resources	**4.97**	0.4	-0.27	-0.09
	13.0%	*1.4%*	*-1.0%*	*-0.3%*

alternative hypothesis that there is a significant difference in means.

It is immediately apparent that the raw data is unbalanced. Nine of the ten illustrative variables demonstrate statistically-significant differences between treated and untreated farms. Seven of the covariates are biased more than 10% between the treated and untreated groups. Treated farms were more than twice as likely to be located in an oil- or gas-producing county than untreated farms.

Figure 4.2: **Reduction of bias with nearest neighbor matching**



All three of the matching algorithms greatly decrease bias relative to the unmatched sample. However, it is worth noting that the kernel-weighted technique still shows a significant difference between treated and untreated farms' likelihood of being in an oil/gas producing county. Since that variable is a strong predictor of energy lease participation, this result is of some concern. Using the nearest neighbor and radius/caliper matching algorithms, we may reject the null hypothesis for all ten illustrative variables.

In addition to differences in means, it is important to consider differing variance across matching algorithms. Matching methods face a trade-off between bias and variance. With large samples such as the TOTAL data set, however, there is often no practical difference in variance between methods (Caliendo and Kopeinig, 2008).

Table 4.12: **Rubin's ratio of variance (covariates orthogonal to the propensity score)**

Selected covariates	**Unmatched**	**Nearest neighbor**	**Radius**	**Epanechnikov kernel**
Acres owned	**0.23**	1.12	**0.72**	**0.60**
Debt-to-asset ratio	**0.71**	0.91	0.92	0.90
Annual hours worked on farm by principal operator	**2.78**	1.01	1.02	1.05
Percent of county over an oil- or gas-bearing shale formation	0.95	0.89	0.94	0.95
High off-farm income (highest quartile in sample)	**1.37**	1.09	1.07	1.08
Located in an oil- or gas-producing county	**0.64**	0.98	0.92	0.91
Percent of land operated that is rented from another landowner	0.81	0.90	0.91	0.90
High-production farm (highest quartile in sample)	1.04	0.96	0.97	0.99
Average county solar irradiation (percentile among U.S. counties)	**1.45**	0.98	1.05	1.04
County contains "good" or better wind resources	0.97	0.99	1.00	1.00

Table 4.12 uses a variance diagnostic table proposed by Rubin (2001). The values listed reflect the ratio of variance for the treated group to the variance for the matched untreated group in the covariates orthogonal to the propensity score. The ratio should close to 1.0 in a balanced sample. As proposed by Rubin, ratios less than 0.8 or greater than 1.2 are cause for concern. Though less pronounced than in Table 4.11, the unmatched sample has clear signs of imbalance, and all three matching algorithms are clear improvements. The nearest neighbor method performs particularly well, with no ratios more than 0.11

from the ideal 1.0.

Finally, Table 4.13 summarizes five joint balancing tests for the matching algorithms tested. The likelihood ratio χ^2 tests the null hypothesis that, controlling for the propensity score, there is no difference in covariate values between the treated and untreated farm groups. The mean and median standardized bias scores summarize imbalance between treated and untreated mean values across all covariates. The ratio of variances is an extension of Rubin's diagnostic described above, summarizing differences in variances across all covariates for treated and untreated farms. Though appealing for their simplicity, joint tests should be considered in conjunction with the variable-by-variable balance tests above; aggregation can conceal problems with important predictors.

Table 4.13: **Joint balancing tests**

Selected covariates	**Unmatched**	**Nearest Neighbor**	**Radius**	**Epanechnikov kernel**
Likelihood Ratio χ^2	3672.2	84.9	37.0	71.0
Mean standardized bias	22.4	2.7	1.8	2.7
Median standardized bias	14.2	2.3	1.5	2.3
Ratio of variances	0.83	0.95	**0.60**	**0.40**

Balance tests of individual covariates and of overall differences in means suggest that the propensity score is a consistent estimate of the (unobservable) true likelihood of a farm receiving energy lease income. Differences in means and variance are minor and manageable. For this study, we opted to continue with the nearest neighbor matching algorithm. For our underlying data, this simple technique offers the best balance of low bias and constant variance between treatment and control groups.

4.5.5 Region of common support

As might be expected, the distribution of propensity scores is very different for participating and non-participating farms.

For our purposes, propensity score matching is only effective if each participating farm can be paired with a non-participating farm that is otherwise very similar. There is no basis for a meaningful comparison if a given farm has a set of characteristics that are always or never associated with energy development.

A common, intuitively appealing approach to defining the region of common support is to simply exclude all treated observations with a propensity score larger than the maximum untreated propensity score and to exclude all untreated observations with a score smaller than the minimum treated propensity score. (See, for instance, Lechner (2002).) We compared the region of common support defined by this approach to those created using two popular alternatives. Cole and Hernán (2008) and Lunt (2014) recommend excluding all subjects with propensity scores in the x^{th} centile of untreated or $100 - x^{th}$ centile of treated groups. Smith and Todd (2005) proposed excluding regions within the distribution with very low density of treated or untreated observations. Balance tests (summarized in Table 4.14) suggest that the Lechner (2002) approach offers the lowest observed difference

Table 4.14: **Methods of defining the region of common support**

Treatment: farm received income from an energy lease in 2014

Method	*Min. prop. score*	*Max prop. score*	*Percent omitted*	*Treated observations*	*Balance test*[1]
No trimming	0	.8868	-	1550	1.8
Minima/maxima[2]	.0002	.7817	0.2%	1550	1.6
Centile-based[3]	.0069	.3828	29.8%	1244	1.9
Density-based[4]	$2.284e^{-7}$	.7907	0.2%	1545	1.8

NOTES: (1) Values in this column represent the median bias in standardized mean values of covariates for treated vs. untreated farms, across all covariates. These estimates used a nearest neighbor matching algorithm, with replacement.

(2) Region of common support defined as the observations with a propensity score greater than the lowest propensity score in the treated group and less than the largest propensity score in the untreated group.

(3) Excludes untreated observations with a propensity score in the 1^{st} centile and treated observations in the 99^{th} centile of propensity scores

(4) Excludes observations with a propensity score more than 0.25 standard deviations of the propensity score from the closest potential match (0.023).

in covariate means, controlling for propensity score, between farms that did and did not receive energy lease payments in 2014.

CHAPTER 5

RESULTS: CHARACTERISTICS OF FARMS PARTICIPATING IN ENERGY LEASING

The following chapter lays out the results from the predictive logistic model described in section 4.2. For ease of reading and comparison, we have grouped covariates into four broad categories: farm business attributes, operator and household attributes, energy resources, and farm location variables (i.e., socioeconomic surroundings).

In the first section below, we look at correlation between covariates and energy production income using the full data set (with clustered errors and population weights as previously described) and three related dependent variables. The dependent variable in the base specification (column 1) simply reflects whether a farm reported *any* income from energy production in 2014. Two variations on that specification focus on energy payments that are "substantial" in either relative or absolute terms. Column 2 limits the treatment group to farms that received at least 50% of their 2014 net farm income from energy production. The dependent variable for column 3 is whether a farm received at least $10,000 in energy payments. In section 5.2, we repeat our analysis while omitting farms classified by the USDA as "residence" operations. The remaining subsample (intermediate and commercial farms in the USDA typology) includes only owner-operators who consider farming to be their primary occupation. Subsection 5.3 compares farm attributes that are associated with participation in an oil or gas lease (of any size) to those associated with other kinds of leases. This analysis uses the full TOTAL sample.

We list the results in terms of the p-score and the average marginal effect on the odds ratio for each independent variable. Results highlighted in green are significant at the $\alpha = .05$ level. The results in this section reflect correlation rather than causation. Where appropriate, we discuss mechanisms that could explain a given result; however, additional study would be necessary to confirm causal relationships.

5.1 All farms: predictors of receiving energy royalties

5.1.1 Farm business variables

Farm size matters across all three specifications. There is a consistent, positive relationship between the number of acres owned by a given farmer and his/her likelihood of reporting energy production income[1]. This is consistent with the findings of Sutherland and Holstead (2014) on wind development, but not with the conclusions of Beckman and Xiarchos (2013) on predictors of commercial-scale solar and Malin and DeMaster (2016) regarding predictors of gas leases in the Marcellus shale[2]. There may a similar, positive relationship between energy income and farmer tenure, as found by Xiarchos and Lazarus (2013) for solar adoption as well as Claassen and Morehart (2009) and Soule et al. (2000) for CRP participation. Farms with lower ratios of land rented to land operated seem more likely to report energy production payments over $10,000, and results are near-significant in the

[1]It seems more likely that greater owned acreage influences likelihood of energy income rather than vice versa. In a separate regression, we replaced the "acres owned" covariate with a covariate reflecting whether the given operation had recently purchased land. We found no evidence of a correlation between energy income and recent farmland purchases, as one would expect if energy development triggered major consolidation in the agriculture (found by Hoy et al. (2018) and Xiarchos (2017)).

[2]This is not necessarily a contradiction; most previous studies focused on a specific type of energy production in a particular area, whereas this thesis is concerned with all energy production on U.S. farmland.

Table 5.1: **Results of predictive model: farm business variables**

	Base (1)		**50% NFI (2)**		**$10K threshold (3)**	
	odds ratio	*p-score*	*odds ratio*	*p-score*	*odds ratio*	*p-score*
Farm debt: more than $250,000	1.395***	*0.007*	1.113	*0.613*	1.471***	*0.004*
Debt to asset ratio	0.610***	*0.008*	0.809	*0.222*	0.534***	*0.006*
Acres owned, in 100s	1.002**	*0.011*	1.002***	*0.000*	1.001***	*0.008*
Conservation payments to farm in 2014	1.370**	*0.030*	1.074	*0.696*	1.105	*0.605*
Percent of acres operated rented from another landowner	0.997*	*0.088*	0.995*	*0.081*	0.990***	*0.000*
Farm specialty: grains or oilseeds	1.328	*0.228*	1.953**	*0.027*	1.528	*0.124*
Value of farm production: lowest quartile	0.846	*0.334*	0.550***	*0.009*	1.130	*0.653*
Farm debt: less than $1000	0.852	*0.365*	0.696	*0.169*	0.518**	*0.013*
Fixed farm costs less than $5000 (approx. lowest quartile)	0.847	*0.515*	0.873	*0.701*	1.054	*0.900*
Value of farm production: highest quartile	0.871	*0.544*	1.386	*0.204*	1.027	*0.924*
Farm specialty: livestock or animal products	1.032	*0.819*	1.039	*0.791*	1.038	*0.849*
Production or marketing contract in place	0.975	*0.873*	0.435***	*0.000*	0.574**	*0.013*
Fixed farm costs ≥ $50,000 (approx. highest quartile)	1.018	*0.898*	1.158	*0.396*	0.958	*0.833*
Farm specialty: fruit or vegetables	1.029	*0.911*	0.694	*0.243*	0.556**	*0.030*

(1) Binary outcome: 1= farm reported income from energy production

(2) Binary outcome: 1= energy production made up more than 50% of net farm income

(3) Binary outcome: 1= farm reported $10,000 or more income from energy production

other two specifications.

There is also a significant relationship between energy income and farm debt (as suggested by Malin and DeMaster (2016)), though the direction of causality is unclear. In two of three specifications, farms with lower debt relative to assets are significantly more likely to report energy production income. High nominal farm debt, though, also appears to be positively correlated with energy income. Farms with more than $250,000 in outstanding debt (approximately the highest quartile for farms in TOTAL) were significantly more likely to report energy income. There is weak evidence of the opposite relationship with low-debt farms. In TOTAL, farm assets would include energy and other non-agricultural assets on land owned by a farm business. Farms with known or suspected energy resources, therefore, would be expected to have greater assets than otherwise comparable operations. This, in turn, would produce a lower debt-to-asset ratio if farms with an energy lease did not leverage their energy resources to the extent of their other assets. However, it is also plausible that farms with less burdensome debt are in a better position to take advantage of development opportunities, and that the correlation with high absolute debt reflects a more fundamental relationship between farm businesses size (or financial sophistication). The non-significant results in Table 5.1 are just as striking. We found no evidence of a relationship between energy leasing and fixed farm costs and very little evidence of a correlation with the value of farm production.

5.1.2 Farm operator and household variables

Since gross farm income in the TOTAL survey includes income from energy production, it is not surprising that farms with a negative net effect on household finances are also less likely to report energy income. However, farms contributing a large share of household income may *also* be less likely to have energy income (this negative correlation is significant in base specification and strongly suggestive in $10,000 case).

It is noteworthy that energy income is strongly associated with high *non*-farm household assets and with high off-farm household income. The effect seems to be stronger

Table 5.2: **Results of predictive model: farm operator and household variables**

	Base (1)		**50% NFI (2)**		**$10K threshold (3)**	
	odds ratio	*p-score*	*odds ratio*	*p-score*	*odds ratio*	*p-score*
Non-farm household assets total ≥ $1 million	1.740***	*0.000*	1.848***	*0.000*	2.505***	*0.000*
Ratio of net farm to total household income: NEGATIVE	0.354***	*0.000*	0.360***	*0.000*	0.113***	*0.000*
Ratio of net farm to total household income: NO RESPONSE	0.145***	*0.000*	0.169***	*0.002*	0.203***	*0.002*
Off-farm household income at least $100,000 in 2013	1.606***	*0.000*	1.858***	*0.000*	2.024***	*0.000*
Farmer experience: more than 10 years	1.489***	*0.003*	1.290	*0.151*	1.279	*0.417*
Ratio of net farm to total household income: HIGH	0.732**	*0.026*	0.852	*0.343*	0.644*	*0.051*
Non-farm debt: high	0.754**	*0.038*	0.674*	*0.089*	1.035	*0.907*
Retirement: plans to retire within 3 years	1.199*	*0.077*	1.226*	*0.095*	1.385	*0.152*
Off-farm household income NEGATIVE in 2013	1.225	*0.161*	1.524*	*0.059*	1.195	*0.464*
Farmer experience: less than 5 years	0.593	*0.184*	0.468	*0.165*	0.355**	*0.012*
Principal operator or spouse graduated 4-year college	1.123	*0.222*	1.153	*0.315*	1.227	*0.166*
Farmer experience: NO RESPONSE	0.681	*0.227*	0.762	*0.492*	0.475*	*0.094*
Female farmer	0.839	*0.426*	0.897	*0.706*	1.027	*0.862*
Risk tolerance: high	1.112	*0.450*	1.248	*0.105*	1.084	*0.766*
Retirement: NO RESPONSE	0.816	*0.546*	0.642	*0.255*	0.709	*0.462*
Principal operator annual hours worked on farm (1000s)	0.979	*0.627*	0.966	*0.612*	0.939	*0.428*
RIsk tolerance: NO RESPONSE	0.902	*0.705*	0.964	*0.924*	0.960	*0.923*
Principal operator has a dwelling on farm operation	0.966	*0.752*	0.681**	*0.038*	1.077	*0.665*
Non-farm debt: none	0.977	*0.854*	0.996	*0.982*	1.827***	*0.001*
Age of primary operator	0.999	*0.917*	0.997	*0.736*	0.991	*0.441*
Non-farm household assets total less than $50,000	1.002	*0.988*	1.139	*0.615*	0.886	*0.738*

(1) Binary outcome: 1= farm reported income from energy production

(2) Binary outcome: 1= energy production made up more than 50% of net farm income

(3) Binary outcome: 1= farm reported $10,000 or more income from energy production

for farms that depend on energy income and for those receiving large energy payments. Households with greater or more diversified assets may be better able to take advantage of development opportunities. Alternatively, households may be investing energy lease income in non-farm assets at the same time that loss of farmed acres to energy production encourages household members to devote more time to off-farm work.

Finally, it is worth highlighting several variables that were not significant in these three specifications. In the full sample, we found no evidence of a relationship between the likelihood of receiving energy production income and an operator's age, education[3], gender, or self-reported risk tolerance. Despite the significant correlation with high off-farm income and assets noted above, we found no corresponding relationship for farms with relatively low off-farm income and assets. Farmers with an energy lease were no more or less likely to report near-term plans for retirement and, perhaps most importantly, did not work significantly fewer hours on their farm. These final (non-) results are not consistent with a hypothesis that energy leases provide an incentive for farmers to exit the industry.

5.1.3 Energy resource variables

Unsurprisingly, state and county energy resource endowments are strong predictors of farm energy income. Overall, there is a clear link between area oil and gas production and the likelihood of a farm having energy production income. The same effect is visible for

[3]Education is strongly significant for intermediate- and commercial-type farms, as will be discussed in Section 5.2.

Table 5.3: **Results of predictive model: energy resource variables**

	Base (1)		**50% NFI (2)**		**$10K threshold (3)**	
	odds ratio	*p-score*	*odds ratio*	*p-score*	*odds ratio*	*p-score*
State natural gas production, MMcf produced per square mile	1.026***	*0.000*	1.029***	*0.000*	1.035***	*0.000*
Natural gas produced in county, 2011 (million cubic feet)	1.000***	*0.000*	1.000***	*0.000*	1.000***	*0.000*
State solar net generation, MWh per square mile	0.967***	*0.000*	0.969***	*0.010*	1.001	*0.959*
Crude oil produced in county in 2011 (1000s of barrels)	1.000***	*0.000*	1.000***	*0.003*	1.000***	*0.000*
Change in county oil production (1000s barrels), 2000 to 2011	1.000***	*0.000*	1.000***	*0.001*	1.000***	*0.000*
Relative county solar resource (percentile of U.S. counties)	1.014**	*0.011*	1.011**	*0.048*	1.020***	*0.001*
County contains "good" or better wind resources	0.768*	*0.073*	0.692**	*0.016*	0.852	*0.317*
State wind net generation, MWh per square mile	1.002	*0.129*	1.002	*0.140*	1.002	*0.154*
State crude oil production, barrels produced per square mile	1.000	*0.209*	1.000	*0.129*	1.000***	*0.009*
Change in county gas production (million cubic feet), 2000 to 2011	0.999	*0.449*	0.999*	*0.087*	0.999	*0.353*
(1) Binary outcome: 1= farm reported income from energy production						
(2) Binary outcome: 1= energy production made up more than 50% of net farm income						
(3) Binary outcome: 1= farm reported $10,000 or more income from energy production						

farms in counties with better solar resources (measured by annual average insolation) and, perhaps, for farms in counties with better wind resources. Clearly, location is important! However, there are some counterintuitive results in this table.

There is no clear relationship between state wind electricity production (adjusted for state area) and the likelihood of energy income for farms. This may be due to the fact that wind development is still much less common than oil or gas drilling. As of July 2018, the U.S. Wind Turbine Database recorded 57,646 wind turbines in the United States (Hoen et al., 2018). In 2016,the most recent year for which statistics are available, the EIA reported 1,010,441 active oil and gas wells (U.S. Energy Information Administration, 2017).

There is also no correlation between energy production income and increasing county gas production from 2000 though 2011 (the most recent year for which county-level gas production data is available). This is likely due the changing geography of U.S. gas production from 2011 to 2014, when ERS collected data for TOTAL. Shale gas production increased by 68% over those three years (U.S. Energy Information Administration, 2018a), so areas of gas production on farmland in 2014 would be somewhat different than areas of oil production in 2011. Furthermore, landowners may be more likely to retain mineral rights for land over unconventional oil and and gas deposits compared to areas with a long history of conventional oil and gas development (Weber and Hitaj, 2015).

Finally, it is striking that farms in states with more solar generation have significantly lower likelihood of reporting energy income. This may reflect a tougher regulatory and policy environment for oil and gas development in states that have prioritized solar development.

5.1.4 Socioeconomic surroundings

After controlling for partisanship, race, and income, there is no obvious correlation between county population density and the likelihood of energy development. Instead, we observed a negative correlation between median county income and receiving energy payments. Farms in more liberal counties also show lower odds ratios than would otherwise be expected. Taken together, these may suggest that wealthier or more liberal areas may

Table 5.4: **Results of predictive model: farm location variables**

	Base (1)		50% NFI (2)		$10K threshold (3)	
	odds ratio	*p-score*	*odds ratio*	*p-score*	*odds ratio*	*p-score*
Cents that state avg retail electricity rate is above or below U.S. avg	1.535***	*0.000*	1.546***	*0.001*	0.781	*0.384*
Cents that state avg retail natural gas rate is above or below U.S. avg	0.734***	*0.000*	0.765***	*0.002*	0.888	*0.192*
County vote for Clinton in 2016 presidential election (%)	0.091***	*0.000*	0.045***	*0.000*	0.253**	*0.049*
Median county household income ($1000s)	0.980**	*0.013*	0.978**	*0.021*	0.976***	*0.000*
County population density	0.999	*0.151*	1.000	*0.387*	0.999	*0.419*
More than 800 internet connections per 1000 households in county by end of 2014	1.179	*0.305*	1.273	*0.300*	0.911	*0.668*
County: percent of population self-identified as "white"	0.997	*0.764*	0.996	*0.660*	1.021**	*0.019*
Fewer than 400 internet connections per 1000 county households by end of 2014	0.945	*0.860*	0.845	*0.594*	1.330	*0.517*

(1) Binary outcome: 1= farm reported income from energy production

(2) Binary outcome: 1= energy production made up more than 50% of net farm income

(3) Binary outcome: 1= farm reported $10,000 or more income from energy production

be less willing to accept nearby energy development–or, rather, the negative externalities that come with it.

At the state level, higher average electricity prices are associated with higher odds of receiving energy income (consistent with Xiarchos and Lazarus (2013) findings on renewable energy adoption) while the reverse is true with average natural gas prices, possibly because natural gas prices are simply lower in production areas. If, however, we impose the $10,000 threshold for substantial energy income, neither electricity nor natural gas prices are significant predictors.

Table 5.5: **Intermediate and commercial farms: farm business variables**

	Base (1)		50% NFI (2)		$10K threshold (3)	
	odds ratio	*p-score*	*odds ratio*	*p-score*	*odds ratio*	*p-score*
Farm debt: more than $250,000	1.586***	0.000	1.522**	0.028	1.452***	0.009
Acres owned, in 100s	1.002***	0.001	1.002***	0.001	1.001***	0.004
Debt to asset ratio	0.565***	0.001	0.588**	0.021	0.509*	0.079
Value of farm production: highest quartile	0.684**	0.010	0.518**	0.021	1.105	0.631
Farm debt: less than $1000	0.539*	0.051	0.417**	0.049	0.387**	0.018
Value of farm production: lowest quartile	1.411	0.187	2.562***	0.003	1.731**	0.049
Percent of acres operated rented from another landowner	0.997	0.190	0.995**	0.026	0.991***	0.000
Principal operator annual hours worked on farm (1000s)	0.947	0.196	0.916	0.174	0.896	0.161
Conservation payments to farm in 2014	1.164	0.279	1.035	0.824	1.012	0.907
Farm specialty: livestock or animal products	0.823	0.306	0.759	0.268	0.800	0.365
Farm specialty: grains or oilseeds	1.223	0.404	1.717*	0.074	1.274	0.348
Fixed farm costs ≥ $100,000 (approx. highest quartile)	1.175	0.662	1.656	0.265	1.660	0.170
Production or marketing contract in place	1.042	0.764	0.533***	0.003	0.622**	0.012
Farm specialty: fruit or vegetables	1.133	0.783	0.989	0.982	0.280**	0.017
Fixed farm costs less than $10,000 (approx. lowest quartile)	1.022	0.873	1.573***	0.005	1.114	0.613

(1) Binary outcome: 1= farm reported income from energy production

(2) Binary outcome: 1= energy production made up more than 50% of net farm income

(3) Binary outcome: 1= farm reported $10,000 or more income from energy production

5.2 Intermediate- and commercial-scale farms

On their own, it's tempting to ascribe some of the effects observed in the full sample to differences between residence-type operations (a large majority of U.S. farms) and intermediate- or commercial-type operations (a large majority of U.S. agricultural production by value). To pick one example, farm debt is strongly correlated with an operations

Table 5.6: **Intermediate and commercial farms: operator and household variables**

	Base (1)		**50% NFI (2)**		**$10K threshold (3)**	
	odds ratio	*p-score*	*odds ratio*	*p-score*	*odds ratio*	*p-score*
Ratio of net farm to total household income: NEGATIVE	0.445***	*0.000*	0.588*	*0.056*	0.231***	*0.000*
Principal operator or spouse graduated 4-year college	1.421***	*0.000*	1.531**	*0.023*	1.541***	*0.001*
Ratio of net farm to total household income: NO RESPONSE	0.157***	*0.002*	0.262**	*0.042*	0.205**	*0.013*
Off-farm household income at least $100,000 in 2013	1.565***	*0.007*	2.339***	*0.000*	2.230***	*0.001*
Farmer experience: more than 10 years	1.612**	*0.028*	1.509*	*0.053*	1.335	*0.187*
Non-farm household assets total ≥ $1 million	1.637**	*0.038*	1.233	*0.258*	1.892***	*0.000*
Non-farm household assets total less than $50,000	1.361**	*0.050*	1.566*	*0.060*	1.016	*0.953*
Female farmer	0.540	0.114	0.619	0.312	0.483**	0.047
Farmer experience: NO RESPONSE	0.482	*0.173*	0.447	*0.238*	0.496	*0.258*
Farmer experience: less than 5 years	0.512	*0.198*	0.245*	*0.075*	0.352	*0.197*
Non-farm debt: none	1.176	0.264	1.231	0.272	1.665***	0.001
Retirement: plans to retire within 3 years	1.219	0.288	1.479	0.127	1.083	0.683
Ratio of net farm to total household income: HIGH	0.870	0.327	1.239	0.300	0.898	0.548
Non-farm debt: high	0.855	0.524	0.714	0.351	1.474	0.207
Principal operator has a dwelling on farm operation	1.071	*0.619*	0.897	*0.622*	1.423*	*0.099*
Retirement: NO RESPONSE	1.210	*0.652*	0.874	*0.817*	0.574	*0.420*
Off-farm household income NEGATIVE in 2013	0.919	*0.664*	1.248	*0.300*	0.595	*0.153*
Age of primary operator	0.996	*0.670*	0.984	*0.239*	0.985	*0.175*
Risk tolerance: NO RESPONSE	0.877	*0.738*	0.629	*0.295*	1.017	*0.976*
Risk tolerance: HIGH	0.996	*0.986*	0.743**	*0.017*	1.084	*0.799*

(1) Binary outcome: 1= farm reported income from energy production

(2) Binary outcome: 1= energy production made up more than 50% of net farm income

(3) Binary outcome: 1= farm reported $10,000 or more income from energy production

scale of production: 65% of the farms in the low debt group are residence operations; 80% of those in the high debt group are commercial in the USDA typology. Even after controlling for related covariates like acres operated, value of production, fixed farm costs, and so forth, results from the full sample could be biased if there are fundamental differences in behavior between part-time and full-time farmers.

In this context, it is important to note that the results for intermediate- and commercial-type farms are very similar to those in the full sample. Nearly all of the covariates that were significant in the full sample were also predictors in this sub-sample: farm acreage, farm debt, contract arrangements, negative farm contribution to household income, non-farm assets, off-farm income, energy resources, county income, and partisanship. Moreover, none of the results from the intermediate- and commercial-type farms contradict those of the full model: no significant covariates "switch signs" between models; positive correlations in one sample are also positive in the other[4].

However, there are some illuminating differences. The relationship between energy income and the value of farm production is much more significant for intermediate and commercial farmers than in the full sample. Interestingly, being in either the lowest or the highest quartile of farm production (within the restricted sample) is associated with a lower likelihood of reporting energy lease income.

Farms with low non-farm household assets also show an elevated likelihood of reporting energy income, a relationship that is not at all apparent in the full sample. This likely

[4]There is one exception among near-significant covariates, the relationship between higher education and energy leasing is positive and significant in the large-farm base specification, but negative in the full sample base specification (with a p-value of 0.184).

Table 5.7: **Intermediate and commercial farms: energy resource variables**

	Base (1)		50% NFI (2)		$10K threshold (3)	
	odds ratio	*p-score*	*odds ratio*	*p-score*	*odds ratio*	*p-score*
Natural gas produced in county, 2011 (million cubic feet)	1.000***	*0.000*	1.000***	*0.000*	1.000***	*0.000*
State natural gas production, MMcf produced per square mile	1.019***	*0.000*	1.023***	*0.000*	1.024***	*0.000*
Change in county oil production (1000s barrels), 2000 to 2011	1.000***	*0.000*	1.000***	*0.000*	1.000***	*0.000*
State solar net generation, MWh per square mile	0.976***	*0.000*	0.980*	*0.066*	1.000	*0.995*
County oil production (1000s barrels), 2011	1.000***	*0.004*	1.000**	*0.018*	1.000***	*0.000*
State wind net generation, MWh per square mile	1.003***	*0.009*	1.002	*0.216*	1.002*	*0.058*
State crude oil production, barrels produced per square mile	1.000*	*0.060*	1.000**	*0.035*	1.000**	*0.013*
Relative county solar resource (percentile of U.S. counties)	1.008	*0.151*	1.008	*0.255*	1.013**	*0.038*
County contains "good" or better wind resources	0.858	*0.236*	0.733*	*0.094*	1.146	*0.323*
Change in county natural gas production (million cubic feet), 2000 to 2011	1.000	*0.859*	0.997**	*0.017*	0.998	*0.407*

(1) Binary outcome: 1= farm reported income from energy production

(2) Binary outcome: 1= energy production made up more than 50% of net farm income

(3) Binary outcome: 1= farm reported $10,000 or more income from energy production

reflects a difference in the relationship between non-farm assets and household net worth for residence farm operators compared to intermediate and commercial farm operators[5] Residence farm households with low non-farm assets are very likely to have low household net worth as well: for residence farms in the total sample, the correlation between non-farm assets and household net worth is .794. Larger farms with low non-farm assets may simply have concentrated their assets in the farm business. For intermediate and commercial farms in our sample, the correlation between non-farm assets and household net

[5]In the USDA typology, the defining characteristic of a residence operation (along with gross production under $350,000) is that the farm's operator does not consider farming to be his/her principal occupation. Farming *is* the principal occupation for operators of intermediate farms and for nearly all operators of commercial-type farms.

Table 5.8: **Intermediate and commercial farms: farm location variables**

	Base (1)		**50% NFI (2)**		**$10K threshold (3)**	
	odds ratio	*p-score*	*odds ratio*	*p-score*	*odds ratio*	*p-score*
County vote for Clinton in 2016 presidential election (%)	0.009***	*0.000*	0.005***	*0.000*	0.030***	*0.000*
Cents that state avg retail electricity rate is above or below U.S. avg	1.450***	*0.000*	1.303	*0.155*	0.898	*0.701*
Cents that state avg retail natural gas rate is above or below U.S. avg	0.782***	*0.001*	0.863*	*0.057*	0.909	*0.300*
Median county household income ($1000s)	0.969**	*0.014*	0.971*	*0.054*	0.953***	*0.000*
More than 800 internet connections per 1000 households in county by end of 2014	1.215	*0.212*	1.639**	*0.022*	1.223	*0.399*
Percent of county residents identifying as white, 2010	0.990	*0.402*	0.972*	*0.056*	1.004	*0.801*
County population density	1.000	*0.482*	1.000	*0.889*	1.001	*0.328*
Fewer than 400 internet connections per 1000 county households by end of 2014	0.880	*0.695*	0.498	*0.105*	0.811	*0.516*

(1) Binary outcome: 1= farm reported income from energy production

(2) Binary outcome: 1= energy production made up more than 50% of net farm income

(3) Binary outcome: 1= farm reported $10,000 or more income from energy production

worth is just .361.

Finally, there seems to be a positive correlation between higher education (by the principal operator or his/her spouse) and energy development.

5.3 Predictors of oil and gas leases

Comparing the attributes of farms with oil and gas leases to those of farms with other types of leases, one is immediately struck by how few independent variables are statistically significant predictors of both. For this section, we regressed each dependent variable (a binary variable reflecting whether the given farm had leased (a) oil and gas rights or (b) other rights) on 53 independent variables. Eighteen attributes were significantly correlated with oil and gas leasing, eleven were correlated with other leases, and just six were correlated with both.

To show the contrast between predictors of these different types of leases, we present the results of the logistic regressions in four tables. In each, we highlight significant, positive correlations in green and significant, negative correlations in purple. The first table contains covariates that were significant with both dependent variables; the second shows those that were significant predictors of oil and gas leases but not other leases; and the third focuses on covariates that were not significant for oil and gas leases, but were significant predictors of leasing other property rights. The fourth table lists the 30 independent variables that were not significant predictors of either.

Once again, the size of a farm is correlated with the likelihood of participating in a lease. Larger operations may suffer less disruption from development of a few acres, parties seeking to lease land or rights may prefer seek out larger blocs of land, or each additional acre may simply increase the odds that some land owned will overlap with resources worth leasing. The proportion of land owned to operated is also significant for

Table 5.9: **Significant predictors of oil/gas *and* other leases**

Oil and gas leases (a)			**Other leases (b)**	
odds ratio	*p-score*		*odds ratio*	*p-score*
1.002***	0.003	***Acres owned, in 100s***	1.001***	0.003
1.573***	0.000	***Non-farm household assets total ≥ $1 million***	1.438**	0.023
1.320**	0.024	***Principal operator or spouse graduated 4-year college***	1.695***	0.000
1.484***	0.001	***State avg retail electricity rate, cents***	1.379***	0.000
0.694***	0.008	***State avg retail natural gas rate, cents***	0.789***	0.001
1.028***	0.000	***State natural gas production, MMcf produced per square mile***	1.009***	0.000

(a) Binary outcome: farm reported oil and gas rights leased for some acres owned

(b) Binary outcome: farm reported other rights leased for some acres owned

oil and gas leasing, and nearly so for other leases (see Table 5.10).

Operators with substantial non-farm assets are also more likely to lease rights for some acres owned. Wealthier households may be in a better position to take advantage of leasing opportunities. Alternately, this result may simply reflect households using farm lease income to accrue non-farm assets.

There is a strong correlation between college graduation and leasing, noteworthy since education is not a significant predictor of energy production income (see Table 5.2).

It is not surprising that state natural gas production is correlated with the likelihood of a farm leasing oil or gas rights. However, it is also correlated with non-oil or gas leases. This is interesting, especially since there is also a significant (negative) association between such leases and average natural gas prices (strongly correlated with regional production) and a near-significant relationship with county-level gas production (see Table 5.10). One possible explanation is “other leases” would include rights leased for activities related to regional oil and gas development (e.g., leasing right-of-way for a pipeline or leasing land for a construction camp). However, if that were the case, we would also expect to see a correlation between non-oil/gas leasing and several other independent variables pertaining to state and county oil production, as well as to changes in county natural gas production. If those correlations exist, they are not obvious in our data. It is also possible that this result, as well as those for the two other state-level covariates in this table, reflect unobserved state-level differences in property rights, regulation, or the prevalence of split estates.

For nearly every covariate in our models, the direction of association was the same for oil and gas leases and other leases. Two notable exceptions are shown in Table 5.10. There is a near-significant correlation between quality of wind resources and non-oil and gas leases, as one would expect for a treatment group that includes wind development leasers. However, farms in such counties are also significantly less likely to lease oil or gas rights, which is difficult to explain. As with energy production more generally, farms in more liberal counties (expressed as percent vote for Hillary Clinton in 2016) are less likely to report oil or gas leasing. However, our results hint at a positive correlation between Democratic lean in a farm’s county and participation in other types of leases, though that association falls well short of significance.

Oil and gas leases, but not other leases, had a negative association with median county household income. This result is consistent with a hypothesis that wealthier areas are less

Table 5.10: **Predictors significant only for oil/gas leases**

Oil and gas leases (a) odds ratio	p-score		Other leases (b) odds ratio	p-score
0.688**	0.034	***County contains "good" or better wind resources***	1.267*	0.068
1.000**	0.014	***County oil production (1000s barrels), 2011***	1.000	0.901
0.150**	0.021	***County vote for Clinton in 2016 presidential election (%)***	2.008	0.300
0.972**	0.014	***Median county household income ($1000s)***	0.986	0.226
1.000***	0.003	***Natural gas produced in county, 2011 (million cubic feet)***	1.000*	0.093
1.357**	0.021	***Off-farm household income at least $100,000 in 2013***	1.299	0.422
0.993***	0.000	***Percent of acres operated rented from another landowner***	0.994*	0.094
0.777**	0.011	***Principal operator has a dwelling on farm operation***	1.014	0.940
0.701***	0.004	***Ratio of net farm to total household income: HIGH***	0.979	0.908
0.557**	0.016	***Ratio of net farm to total household income: NEGATIVE***	0.753	0.152
0.200***	0.000	***Retirement: NO RESPONSE***	0.366	0.179
0.461**	0.015	***Risk tolerance: NO RESPONSE***	0.665	0.477

(a) Binary outcome: farm reported oil and gas rights leased for some acres owned

(b) Binary outcome: farm reported other rights leased for some acres owned

willing to accept or more able to block development on farmland with potential negative externalities.

The association noted in Sections 5.1 and 5.2 between energy income and high off-farm income is present, here, for oil and gas leases. Since rent and payments from an oil and gas lease would be considered on-farm income, this suggests that households with high off-farm income may be more willing or able to use part of their agricultural land

Table 5.11: **Predictors significant only for *non*-oil/gas leases**

Oil and gas leases (a)			**Other leases (b)**	
odds ratio	*p-score*		*odds ratio*	*p-score*
1.265	0.138	***Conservation payments to farm in 2014***	1.807***	0.002
1.207	0.202	***Farm debt: more than $250,000***	1.883**	0.019
1.019	0.873	***Farm specialty: livestock or animal products***	0.639***	0.002
1.006	0.510	***Relative county solar resource (percentile of U.S. counties)***	1.019***	0.000
0.967*	0.052	***State solar net generation, MWh per square mile***	0.978***	0.000

(a) Binary outcome: farm reported oil and gas rights leased for some acres owned

(b) Binary outcome: farm reported other rights leased for some acres owned

for energy development. Supporting this view, there is also a negative correlation between oil and gas leasing and high household dependence on farm income. Operators with less non-farm income seem just as likely to sign other types of leases, which would include leases of property rights that would not disrupt farming (e.g., hunting or water access), as those relying on off-farm income.

Farm operators that live on their farmland are significantly less likely to have an oil and gas lease. Just as studies of non-operating landlords by Hitaj et al. (2018) and Bigelow et al. (2016) demonstrated that more distant landowners were more likely to lease oil and gas rights, owner-operators that live off-site may be less vulnerable to negative quality of life impacts from oil and gas development.

Turning to predictors that were significant only for non-oil and gas leases, we see a somewhat unusual relationship with area solar production. Farms are more likely to report *non*-oil or gas leases in counties with relatively good solar resources, which could reflect solar development or recreation-related leases in sunnier areas. There is a near-significant negative association between state solar generation and oil and gas leasing, which seems similar to an effect noted above for energy production income. However, farms in states with more solar generation are also less likely to report other types of leases, which is difficult to explain.

Farms that received payments from federal conservation programs in 2014 were more likely to have leased non-oil or gas rights. At first glance, this is surprising. In rental payment programs like the Conservation Reserve Program (CRP) and Conservation Reserve Enhancement Program (CREP), the USDA pays farmers to remove sensitive land from production and undertake conservation work. CRP and CREP participants accept limits on their rights to use or develop covered land. Cost-sharing conservation programs like the Environmental Quality Incentive Program (EQIP) and Conservation Stewardship Program (CSP) provide technical and financial assistance to farmers adopting more sustainable agricultural practices, aiming to increase farmland productivity while decreasing negative environmental impacts. Both EQIP and CSP require participants to invest their own funds, and program interventions are intended to increase the per-acre productivity of participants. It would be surprising for program participants to forego these benefits by leasing out improved farmland for a non-agricultural use. One possible explanation is that land covered by CRP and CREP may be more attractive for hunting and other recreational uses; the USDA explicitly allows participants to lease such rights on covered land. Alternately, productivity-enhancing programs like EQIP and CSP may encourage operators to devote more time and other resources to their most best land, freeing up more marginal farmland for other uses.

High debt (in absolute terms) was a significant predictor of energy income in 5 of 6 model specifications laid out in Sections 5.1 and 5.2. Here, however, we only observed a correlation with non-oil and gas leases.

Table 5.12: **Significant predictors of *neither* oil/gas nor other leases**

Oil and gas leases (a)			**Other leases (b)**	
odds ratio	*p-score*		*odds ratio*	*p-score*
1.001	0.821	***Age of primary operator***	1.003	0.706
1.000	0.934	***Change in county natural gas production (million cubic feet), 2000 to 2011***	1.001	0.834
1.000	0.118	***Change in county oil production (1000s barrels), 2000 to 2011***	1.000	0.743
1.000	0.780	***County population density***	0.999	0.213
0.926	0.741	***Debt to asset ratio***	0.489	0.415
0.803	0.175	***Farm debt: less than $1000***	0.887	0.764
0.836	0.502	***Farm specialty: fruit or vegetables***	0.889	0.787
1.079	0.653	***Farm specialty: grains or oilseeds***	0.785	0.382
0.867	0.693	***Farmer experience: less than 5 years***	0.498	0.200
1.093	0.548	***Farmer experience: more than 10 years***	1.067	0.679
1.086	0.828	***Farmer experience: NO RESPONSE***	0.659	0.341
0.896	0.673	***Female farmer***	0.937	0.756
1.045	0.891	***Fewer than 400 internet connections per 1000 households***	1.098	0.786
0.772*	0.100	***Fixed farm costs greater than $50,000 (highest quartile)***	0.802	0.468
1.047	0.862	***Fixed farm costs less than $5,000 (lowest quartile)***	0.576	0.114
1.136	0.448	***More than 800 internet connections per 1000 households***	1.215	0.151
0.704*	0.070	***Non-farm debt: high***	0.808	0.377
0.910	0.539	***Non-farm debt: none***	0.893	0.419
1.079	0.644	***Non-farm household assets total less than $50,000***	1.107	0.644
1.183	0.358	***Off-farm household income NEGATIVE in 2013***	0.922	0.765
1.000	0.980	***Percent of county residents identifying as white, 2010***	1.013*	0.063
1.015	0.729	***Principal operator annual hours worked on farm (1000s)***	1.092	0.238
0.841	0.292	***Production or marketing contract in place***	1.113	0.484
0.396	0.110	***Ratio of net farm to total household income: NO RESPONSE***	0.894	0.852
1.168	0.338	***Retirement: plans to retire within 3 years***	1.266	0.248
1.070	0.609	***Risk tolerance: HIGH***	1.091	0.629
1.000	0.400	***State crude oil production, barrels produced per square mile***	1.000	0.141
1.001	0.621	***State wind net generation, MWh per square mile***	1.001	0.166
1.203	0.350	***Value of farm production: highest quartile***	0.928	0.829
0.797	0.205	***Value of farm production: lowest quartile***	1.087	0.703

(a) Binary outcome: farm reported oil and gas rights leased for some acres owned

(b) Binary outcome: farm reported other rights leased for some acres owned

CHAPTER 6

RESULTS: IMPACTS OF ENERGY LEASE INCOME ON PARTICIPATING FARMS

Under the assumptions described in Chapter 4, propensity score matching permits causal inference of the impacts of income from energy production on participating farms' financial characteristics. Energy production income clearly had a positive effect on some operations: treated farms were more likely to make capital investments, more likely to report net farm income over $100,000, and less likely to report negative net farm income. Overall, however, energy production income had no significant effect on the amount of per-operation capital investment, total net farm income, or the presence of credit constraints. The results below reflect the average treatment effect on the treated.

Farms with energy production income were consistently more likely to report some capital spending, but we observed little difference in the amount invested by treated farms compared to their near-peers in the control group. The former result suggests that energy production income is important for some operations that could not otherwise justify or afford capital investment; the latter result, however, leads us to believe that this effect is trivial when looking at per-operation capital investment by farms more broadly. The coefficient of capital spending is positive in both the base specification (Table 6.1) and when limiting the treatment group to energy income over $10,000 (Table 6.3). Nevertheless, both fall well short of statistical significance. The correlation was significant in only one specification, in which the treatment group was confined to farms receiving a large proportion of their net farm income from energy production (Table 6.2).

Table 6.1: **Financial impacts: received *any* energy production income**

Outcome	**Coefficient**	**Stand. Error**	**P-value**	**Common support**
Likelihood of investing in capital assets	0.132	0.016	0.000	*29,696*
Amount spent on capital	$15,428	$14,517	0.288	*18,800*
Total net farm income	$12,475	$38,826	0.748	*29,696*
Net farm income: over $100,000	0.119	0.017	0.000	*29,696*
Net farm income: negative	-0.065	0.016	0.000	*29,696*
Farm is credit constrained	-0.002	0.008	0.770	*25,903*

Treatment group: farms reporting income from energy production

Table 6.2: **Financial impacts: 25% of net income from energy production**

Outcome	**Coefficient**	**Stand. Error**	**P-value**	**Common support**
Likelihood of investing in capital assets	0.131	0.023	0.000	*29,726*
Amount spent on capital	$31,376	$14,409	0.029	*18,802*
Net farm income results presented separately				
Farm is credit constrained	-0.007	0.010	0.492	*25,878*

Treatment group: farms receiving at least 25% of net farm income from energy production

Table 6.3: **Financial impacts: received ≥ $10,000 energy production income**

Outcome	**Coefficient**	**Stand. Error**	**P-value**	**Common support**
Likelihood of investing in capital assets	0.166	0.024	0.000	*29,697*
Amount spent on capital	$38,832	$30,067	0.197	*18,800*
Net farm income	$98,150	$82,839	0.236	*29,697*
Net farm income: over $100,000	0.247	0.025	0.000	*29,697*
Net farm income: negative	-0.141	0.024	0.000	*29,697*
Farm is credit constrained	-0.011	0.011	0.317	*25,904*

Table 6.4: **Impacts on intermediate and commercial farms receiving energy production income**

Outcome	**Coefficient**	**Stand. Error**	**P-value**	**Common support**
Likelihood of investing in capital assets	0.042	0.017	0.017	*17,795*
Amount spent on capital	$1,050	$13,082	0.936	*13,126*
Net farm income	-$80,974	$56,142	0.149	*17,795*
Net farm income: over $100,000	0.025	0.024	0.293	*17,795*
Net farm income: negative	-0.027	0.021	0.201	*17,795*
Farm is credit constrained	0.007	0.010	0.462	*15,723*

Energy production income also did not demonstrably increase per-operation net farm income[1]. Treated farms were, however, more likely to be in the high-income group and less likely to report negative net farm income.

There is no evidence that energy production income relieved credit constraints. In all of our specifications, treated farms were no more or less likely to report difficulty borrowing.

After removing residence-type farms from the sample (see Table 6.4), energy production income had a positive impact on the likelihood of farms investing in capital assets. The apparent size of the effect and the statistical significance were, however, weaker than in the full sample. We observed no other significant effects from energy income for intermediate and commercial farms. In this context, it is important to remember that energy produc-

[1]The "25% net farm income" case is an exception, almost by definition. For farms with low or negative profits from agriculture, any amount of energy production will make up a large percent of net income.

	Coef.	S.E.	P	Common sup.
Net farm income	-$180,552	$42,669	0.000	*29,726*
Net farm income: over $100,000	-0.024	0.020	0.238	*29,726*
Net farm income: negative	0.149	0.024	0.000	*29,726*

Table 6.5: **Impacts of oil and gas leases vs. other leases**

Oil or gas leases				
Outcome	**Coefficient**	**Standard Error**	**P-value**	**Common support**
Likelihood of investing in capital assets	0.129	0.019	0.000	*18,925*
Amount spent on capital	$5,923	$16,719	0.723	*13,673*
Net farm income	-$14,931	$42,682	0.726	*18,925*
Net farm income: over $100,000	0.032	0.023	0.155	*18,925*
Net farm income: negative	-0.007	0.021	0.721	*18,925*
Farm is credit constrained	-0.006	0.010	0.550	*16,672*
All other leases				
Outcome	**Coefficient**	**Standard Error**	**P-value**	**Common support**
Likelihood of investing in capital assets	0.120	0.028	0.000	*18,945*
Amount spent on capital expenses	$20,801	$19,314	0.281	*13,702*
Net farm income	$34,952	$76,354	0.647	*18,945*
Net farm income: over $100,000	0.077	0.037	0.040	*18,945*
Net farm income: negative	-0.046	0.033	0.156	*18,945*
Farm is credit constrained	-0.013	0.015	0.070	*16,689*

tion income is a small part of gross income for most treated farms: among intermediate- and commercial-type farms reporting energy income, the median annual payment was just $7,000. The energy payments may simply be too small for farm operators, particularly those with intermediate- and commercial-type farms, to factor into investment decisions.

Comparing farms with oil or gas leases to those leasing other rights (see Table 6.5), we found again that both types of leases led to a higher likelihood of capital investment. For farms with an oil and gas lease, we found little evidence of other impacts on farm finances. For other leases, however, our findings suggest an increased likelihood of the leasing farm having high net farm income.

CHAPTER 7

CONCLUSIONS, IMPLICATIONS, AND NEXT STEPS

7.1 Impact of energy leasing on farms

Our results suggest that, in the broadest terms, the true impacts of energy development on farmland are more complex than either of the popular narratives laid out in the introduction. There is certainly little evidence of farmers with energy leases on average winding down their operations or planning for a long-term reduction in output. However, it also seems that the benefits of energy leasing are small for most host farms. Energy production income encourages reinvestment by some farms, but has a negligible effect on the average amount of capital investment by treated farms. Farms with energy leases are less likely to report negative net farm income and more likely to report farm income over $100,000 than peers with comparable characteristics but, at the same time, energy production income has little apparent impact on mean net farm incomes. As a whole, energy development does not seem to be either a threat or a panacea for participating farms, let alone the broader agricultural economy.

7.2 Predictors of energy lease participation

Energy production leases are more common among larger operations and wealthier farm households. Acres owned, off-farm income, and non-farm assets were consistently significant predictors of energy income.

The operator's personal characteristics were less significant than anticipated. We found little evidence of a significant correlation between the likelihood of a farm having energy income and the farm operator's age, risk tolerance, time spent farming, or retirement plans. Education was a significant predictor, but only for larger farms.

Table 7.1: **Summary of significant correlation between dependent and selected independent variables**

Covariate is significant in: more specifications ↑ … ↓ fewer specifications

Covariate	Significant in # of specifications	Category
Acres owned	6 of 6	Farm business
High off-farm income	6 of 6	Operator & household
County gas productio	6 of 6	Energy resources
County oil production	6 of 6	Energy resources
Partisan lean	6 of 6	Area attributes
High debt	5 of 6	Farm business
High non-farm assets	5 of 6	Operator & household
Median income	5 of 6	Area attributes
Debt to asset ratio	4 of 6	Farm business
Production contract	4 of 6	Farm business
County solar resource	4 of 6	Energy resources
Electricity prices	4 of 6	Area attributes
High production	2 of 6	Farm business
High risk tolerance	1 of 6	Operator & household
County wind resource	1 of 6	Energy resources
Age	0 of 6	Operator & household
Retirement plans	0 of 6	Operator & household
Low internet access	0 of 6	Area attributes
Population density	0 of 6	Area attributes

Note: based on results for all farms in section 5.1 and intermediate-/commercial-type farms in section 5.2

Location is important in several ways. Unsurprisingly, the energy resources in a farm's area affect the likelihood of energy leasing. Greater regional hydrocarbon resources and production intensity strongly predict energy leasing. Solar resource quality is also associated with higher leasing likelihood, though more weakly. However, the relationship is ambiguous for wind resources and farms in states with more solar net generation (adjusted for state area) are actually *less* likely to report an energy lease, possibly due to more demanding regulation of oil and gas development in states that have emphasized solar expansion.

Less obviously, differences in county-level socioeconomic characteristics are also tied to the likelihood of energy development. We observed a strong relationship between a county's vote in the 2016 presidential election and energy leases on its farmland. Farmers in more Democratic-leaning counties were significantly less likely to report energy production income than would otherwise be expected. There is strong evidence of a similar association affecting farms in counties with higher median household income, possibly evidence that wealthier communities are less willing to accept (or more effectively oppose) nearby energy development.

7.3 Implications for farmers, planners, and developers

Are energy leases good for farmers? Our results suggest a resounding "maybe." Farms with energy leases are more likely to turn a profit and to make capital investments. However, energy leases tend to be associated with larger and wealthier owner-operators rather than with operations that might otherwise struggle to break even or invest in future productivity. Interventions that give such operations more access to energy development opportunities could be beneficial. In a similar vein, extension services and farm agencies could expand training for farmers interested in energy leasing and help to connect energy developers to appropriate partners.

Nevertheless, stakeholders should not anticipate energy development to dramatically change the circumstances of most host farms, let alone impact the local agricultural economy. Energy production income is typically a small contribution to household income with little impact on a farm's overall financial outlook. In particular, it does not seem to be a solution for farms facing limited or no access to credit. If the overall benefits to U.S. farmers are limited, though, so are the overall costs. There is little evidence that energy development has adversely affected host farms. There is no apparent negative impact on net income or on capital investments.

7.4 Next steps

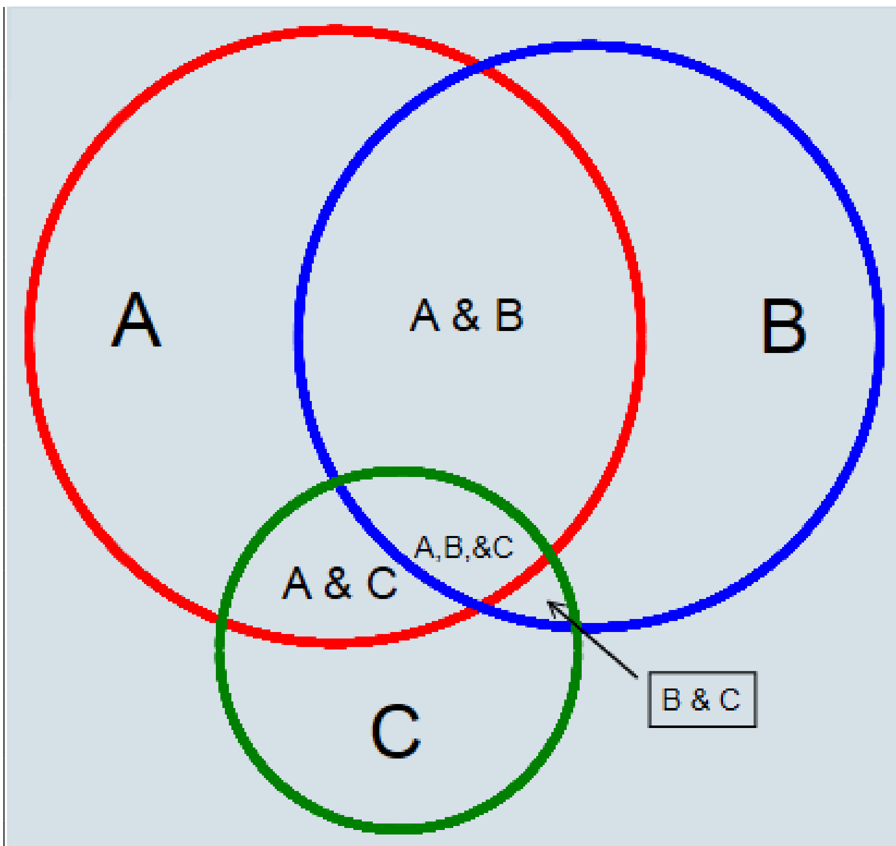
The TOTAL survey of non-operating agricultural landlords offers an opportunity to perform similar analysis, identifying landowner attributes associated with higher likelihood of leasing land for energy development. Those findings, in turn, could clarify the likely consequences of energy development on the availability and price of rented farmland.

In the longer term, new surveys could fill in many of the gaps left at the conclusion of this study. TOTAL data provides an excellent snapshot of participating farms in 2014, but is an imperfect source for studying effects over time. This study also cannot differentiate between different types of energy production, and does not consider income from energy-related facilities like pipelines, transmission corridors, and construction staging grounds. Additional data may be necessary to demonstrate causal relationships for the independent variables used in the predictive logistic model and to address the risk of omitted variable bias in the PSM model.

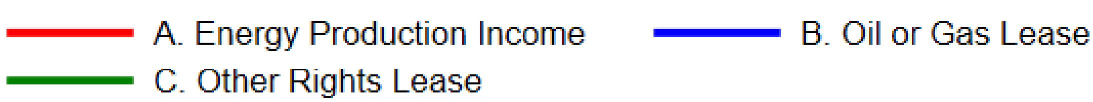
APPENDIX A

OVERLAP BETWEEN TREATMENT GROUPS

Table A.1: **Overlap Between Treatment Groups**



A only:	701
B only:	655
C only:	283
A ∩ B	707
A ∩ C:	210
B ∩ C:	106
A ∩ B ∩ C:	68



We based the treatment groups in this study on questions 555, 7020, and 7026 from the TOTAL questionnaire. These questions, respectively, asked respondents to report income from “royalties or leases associated with energy production (e.g. natural gas, oil, and wind turbines)”; acres of owned land with the oil and gas rights leased out; and acres of owned land with other rights leased out. There is substantial overlap between these treatment groups, as shown in Figure A.1. Of the 29,733 observations in the TOTAL data set, 2,526 are in one or more treatment groups.

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