

Assessment of IRP Truck Licensing for Ohio Counties

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16. Abstract Ohio officials are concerned with the disconnect causing an IRP revenue shortfall. County governments and taxing districts are not given enough IRP revenue to correct the amount of pavement damage caused by commercial vehicles on local roads. Researchers determined the disconnect stems from a combination of Ohio's IRP distribution process and the growing phenomenon of "jurisdiction shopping", which is where companies register trucks in an IRP jurisdiction that is not the vehicle's primary domicile location. Doing this saves the company money on non-IRP taxes and fees. Although IRP fees are still apportioned based on miles traveled, the money is distributed to counties and taxing districts differently than if the vehicle was registered in Ohio. Currently, there are more than 20,000 vehicles belonging to a company with a primary address in Ohio, but registered in another jurisdiction. The result is significant revenue impacts on Ohio counties, municipalities, and townships. In 2015, we predict the direct and indirect impacts will be \$10.13 million for counties, \$2.89 million for municipalities, and \$684,997 for townships. The cumulative effect for all counties and taxing districts is as much as \$13.7 million, although the true impact is potentially higher when additional factors are taken into account.					
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Executive Summary

Project Background

Local government officials in Ohio perceived an imbalance between the percentage of International Registration Plan (IRP) revenue allocated to counties and taxing districts, and the amount of pavement damage caused by commercial vehicles on local roads. The problem is twofold: not only are local revenue allocations from IRP vehicle registration fees insufficient, but local roads are more susceptible to accelerated deterioration due to their pavement design, which differs from that of high-traffic state and federal roads. The allocation problem is a result of both the complex manner in which Ohio allocates its vehicle license tax and the loose requirements for declaring a base jurisdiction with IRP authorities.

IRP policy dynamics are substantially more complex than they appear at first glance. For most jurisdictions, a carrier's base jurisdiction is largely irrelevant as long as they accurately report accrued mileage, which is used to apportion fees. Provided that other jurisdictions do not offer commercial truck registration enticements that violate IRP bylaws (this phenomenon is referred to as jurisdiction shopping, although it indirectly impacts other taxes and fees), there should not be a significant effect on a jurisdiction's apportioned revenue, which it receives from other IRP members. While the state-level revenues are largely unaffected by IRP apportionment, the story is different for counties, municipalities, and townships in Ohio. Ohio's state code has two separate allocation policies for IRP revenue. One policy applies to revenue generated by in-state registrations, the other policy for revenue that comes from other jurisdictions.

Jurisdiction shopping has become more prevalent, particularly for large trucking firms. Some Ohio taxing districts with large fleets have seen sharp IRP revenue decreases, and they have struggled to maintain local roads. The fiscal crunch is felt by county engineers, who are pressured by prospective trucking or trucking-related businesses and economic development agencies to enhance roadways or upgrade traffic control systems. The key to fixing the system is to identify the manner in which the registration issues are impacting the revenue streams in Ohio counties (and the taxing districts situated therein) and what might be done to eliminate, or at least limit, revenue losses in those counties. This report will identify the problems with current IRP revenue allocation and will assess the impact on Ohio counties and taxing districts.

Study Objectives

The study goal was to demonstrate how distributable IRP revenue works under the current model. The research assessed current registration trends, translated those registration trends into revenue trends and forecasts, calculated IRP revenue impacts due to jurisdiction shopping, and provided case studies that further demonstrated the intricacies of IRP tax distribution not addressed by the statewide estimates. Ultimately, the purpose of the study was to determine whether the revenue impact is significant enough to warrant further investigation of IRP tax distribution alternatives. This research will be used to assess how Ohio-based commercial vehicle fleets registered in other states can impact the stream of IRP revenues for Ohio counties, townships, and municipalities.



Description of Work

Researchers gathered data about IRP truck registrations, distributable IRP revenue, and tax distribution mechanisms. Revenue is tabulated for each Ohio county and their constituent taxing districts from 2009 to 2013 (or in some cases, 2014). The researchers calculated the county-level retention of direct IRP registrations, IRP loss compensation, and the annual excess compensation fund. By using revenue trends, IRP impact was forecasted from 2015 to 2019. Using national IRP fleet data, the research team determined the number of vehicles belonging to Ohio-based carriers and registered in another IRP jurisdiction. Using a weighted vehicle weight (as specific vehicle weights were not available for these trucks), the FY 2015 impacts were calculated based on the county location of each carrier. Additional information was gathered via surveys of County Engineers and county-specific investigation. This information was used, along with the forecasts and 2015 IRP revenue impacts, to create an extrapolated five-year impact assessment for Clinton, Mahoning, Butler, and Franklin Counties.

As a result of this work, an IRP licensing impact study was created and written to explain the project background, Ohio's tax distribution policy, registration trends, revenue trends, impacts, and county-specific case studies. For the IRP licensing methodology, the research team created an IRP calculator for county engineers that allows them to enter fleet information and estimate the revenue impacts to their own county if a large firm should decide to engage in jurisdiction shopping in the future.

Research Findings & Conclusions

In 2015, the statewide revenue effect for Ohio's counties and taxing districts was just under \$13.7 million. The jurisdiction-shopping impact for Ohio's 88 counties was \$10.13 million, with \$8.23 million in direct effects and \$1.9 million in indirect effects. Municipalities were negatively impacted by \$2.89 million, all in direct effects. Total township impacts were \$684,997, with \$6,633 in direct impacts and \$678,364 in indirect impacts. These estimates assume that every potential out-of-state truck registration is repatriated to every county. The direct, county-specific impacts (excluding townships, municipalities or indirect county impacts) vary greatly from county to county. In 14 counties, there was no impact; another 38 counties saw an impact of less than \$10,000. Seventeen counties had revenue displacement between \$10,000 and \$49,999. The next nine counties faced more substantial losses: between \$50,000 and \$99,999. We estimated that four counties would lose between \$100,000 and \$199,999 in registration fees. Three other counties lost between \$200,000 and \$600,000. The three most-impacted counties were Clinton County (\$3.13 million), Franklin County (\$1.45 million), and Hamilton County (\$822,916). Thus, the most significant impacts were concentrated in 19 Ohio counties. We did not produce estimates for each township and municipality.

Recommendations for Implementation of Research Findings

If a Phase II study is approved, Ohio officials and the research team will need to consult about potential marketing strategies and tools to approach this problem, as well as about long-term state strategies available to improve IRP distributions. The technical advisory committee will need to decide: (1) whether to pursue a solution that solely addresses the distribution equity or one that tackles the economic development issue; (2) whether the excess annual compensation funds should be used to remediate problems with equity or if another source of funding is preferable; (3) if a



reporting mechanism for domiciled vehicles should be established so that it is easier for Ohio County Engineers to address jurisdiction shopping; (4) on policy solutions that best addresses the issue; and (5) on the general direction for the types of marketing strategies and tools most useful to engineers. The research team developed an IRP fleet impact estimator, which Ohio County Engineers can use to estimate the impact of a fleet in their county who will be shifting its registrations to another state. The calculator lets users select the county from a drop-down menu before inputting the fleet information. The tool estimates the impact on the county, township, and municipalities where the carrier is located. The calculator uses the same methodology as the impact assessment in Chapter 3.

Chapter 1. Introduction

Ohio is a member of the International Registration Plan (IRP), a registration reciprocity agreement for commercial vehicle fleets that travel between its member jurisdictions. The 48 states, District of Columbia, and 10 Canadian provinces that are members of IRP are commonly referred to as jurisdictions by transportation officials. Commercial carriers register with a base jurisdiction and report mileage totals logged within each state and/or province to the base jurisdiction. Registration fees are apportioned based on the percentage of miles logged in each jurisdiction. Each month, nearly all jurisdictions participate in a funds netting process whereby fees are transmitted through the IRP Clearinghouse.¹ In Ohio, the Department of Public Safety (ODPS) coordinates the apportionment process and distributes the registration revenue to Ohio counties, townships, and municipalities (also known as taxing districts).

Local government officials in Ohio perceived an imbalance between the percentage of IRP revenue allocated to their governments from registration fees and the amount of pavement damage caused by commercial vehicles on local roads. The problem is twofold. Not only are local revenue allocations from IRP insufficient, but local roads are especially susceptible to accelerated deterioration due to their pavement design, which differs from that of high-traffic state and federal roads. The allocation problem is a result of both the complex manner in which Ohio allocates its vehicle license tax and the loose requirements for declaring a base jurisdiction with IRP authorities.

IRP policy dynamics are substantially more complex than they appear at first glance. For most jurisdictions, a carrier's base jurisdiction is largely irrelevant as long as they accurately report accrued mileage, which is used to apportion fees. Provided that other jurisdictions do not offer

¹ New Brunswick, Oklahoma, and Oregon are the exceptions.

vehicle registration enticements that violate IRP bylaws (this phenomenon is referred to as jurisdiction shopping, although it indirectly impacts other taxes and fees) there should not be a significant effect on a jurisdiction's apportioned revenue, which it receives from other IRP members. While the state-level revenues are largely unaffected by IRP apportionment, the story is different for counties, municipalities, and townships in Ohio. Ohio's state code has two separate allocation policies for IRP revenue. One policy applies to revenue generated by in-state registrations, the other for revenue that comes from other jurisdictions. Jurisdiction shopping has become more prevalent, particularly for large trucking firms. Some Ohio taxing districts with large fleets have seen sharp IRP revenue decreases, and have struggled to maintain local roads. The economic crunch is felt by county engineers, who are pressured by prospective trucking or trucking-related businesses and economic development agencies to enhance roadways or upgrade traffic control systems. The key to fixing the system is to identify the manner in which the registration issues are impacting the revenue streams in Ohio counties (and the taxing districts situated therein) and what might be done to eliminate, or at least limit, revenue losses in those counties. This report identifies the problems with current IRP revenue allocation and assesses their impact on jurisdictions.

1.1 Research Context

In most IRP jurisdictions, the base (or home) jurisdiction of a carrier operating in the state is largely irrelevant as long as the carrier accurately reports accrued mileage, which is used to apportion fees. Provided that other jurisdictions do not offer registration enticements that violate IRP bylaws (the phenomenon of jurisdiction shopping, though it does indirectly impact other taxes and fees), this should not have a substantial effect on a jurisdiction's apportioned revenue, which it receives from other IRP members. There are two slight exceptions. During the initial registration

period, some carriers make substantial efforts to register in a state with low plate fees. This is because first-year carriers often use estimated mile calculations provided by the jurisdiction, and a large percentage of the plate fee will be apportioned to the jurisdiction in which new carriers register. If a carrier registers in Indiana but operates mostly in Ohio, the carrier will send most of its money to Indiana during the first year if it uses Indiana's mileage estimates for first-year firms. However, the base jurisdiction claimed by a carrier should not impact the revenues sent to other jurisdictions after the first year of operation. Thereafter, plate fees are distributed based on actual miles logged, and the fees paid to each jurisdiction in which the carrier operates would be the same irrespective of which jurisdiction serves as the base jurisdiction (again, assuming the carrier's mileage reports are accurate). The other exception pertains to the Highway Safety Fee portion of Ohio's license tax. For Ohio-based trucks, this fee is not apportioned. The corresponding amount that other state jurisdictions collect from their trucks on Ohio's behalf is apportioned.

While state-level revenues are largely unaffected by IRP apportionment, the story is different for Ohio taxing districts. Ohio's state code establishes a different allocation policy for IRP revenue generated by in-state registrations than for IRP revenue that originates in other jurisdictions. Ohio's IRP allocation policy for apportioned vehicles registered in another jurisdiction, which is spelled out in ORC 4501.044, specifies rules for allocating this revenue to counties, municipalities, and townships. This creates winners and losers because taxing districts with trucks registered in Ohio will also receive out-of-state revenue through the loss compensation process described in Chapter 2. Taxing districts that have lost truck registrations to other states get very little out-of-state revenue for those vehicles because the bulk of IRP revenue distributions are tied to whether a vehicle is registered in Ohio. Because of the prevalence of jurisdiction shopping, particularly among large trucking firms, some Ohio taxing districts where large fleets are domiciled have seen

sharp IRP revenue declines. Consequently, they are struggling to maintain local roads with these diminishing revenue streams.

1.2 Previous Research

IRP taxes, fees, laws, regulations and processes vary greatly from state to state. Policy diffusion — the manner in which a public policy is transmitted from one county, state, or local government unit to another — can influence the behavior of jurisdictions. Karsch (2007) identifies four primary diffusion mechanisms: geographic proximity, imitation, emulation, and competition. In short, a jurisdiction is more likely to adopt a particular policy from another jurisdiction if that jurisdiction is located in an adjacent state or county, has similar attributes which could therefore lead to similar policy outcomes, is attempting to implement a policy because it has enjoyed success elsewhere, or is trying to compete with another jurisdiction for purposes of economic development.

A 2003 Texas Transportation Institute (TTI) study of heavy truck registration demonstrated the presence of these patterns. The study compared the success of Oklahoma in attracting a large number of IRP truck registrations, while Texas IRP truck registrations stagnated. The history and success of Oklahoma's policy, the questionable legality surrounding the practices of some trucking companies registering there, and the subsequent legal disputes between IRP member jurisdictions underscores the competition between states to attract carriers (Jasek, Ojah, and Hoover, 2003). The study usefully distinguished between fraudulent and legitimate jurisdiction shopping. Fraudulent jurisdiction shopping occurs when a trucking firm sets up registration in a state where it has not established a legitimate place of business. Typically, these firms use the addresses of permitting services, or potentially a non-physical address, such as a post office box. After an IRP peer review of Oklahoma, IRP rules were changed to require that employees be physically present at the location(s) used. Permitting services were no longer counted as a place of business. However,

legitimate jurisdiction shopping was permissible, and firms operating terminals or locations in multiple jurisdictions have several registration options. Likewise, officials in Ohio have made significant changes to truck registration procedures and policies so the state can compete with Indiana, a bordering state that has adopted several business-friendly laws and regulations to pursue trucking industry investment.

In broader practice, the decision to register a vehicle in a particular jurisdiction entails several considerations not always directly related to IRP fees. These decisions exert a large financial and administrative impact on the motor carrier. When trucking firms register their vehicles in a jurisdiction, they are subject to various state or provincial taxes and fees, licensing requirements, policies, procedures, and regulations. Laws, regulations, and taxes enacted at the local level may also apply. Interviews conducted with trucking industry representatives as part of TTI's study indicated that trucking companies consider the effects of regulation, taxes, fees, administrative burden, and quality of customer service when jurisdiction shopping (Jasek, Ojah, and Hoover, 2003). The TTI study advances several suggestions that Texas — or by logical extension, any state — could use to improve its policies in order to repatriate IRP registrations (and all associated taxes and fees). Carriers interviewed as part of the Texas study expressed concerns about the ad valorem tax and the sales tax associated with the purchase of new tractors or trailers. As of 2002, Oklahoma had no ad valorem tax, sales tax for commercial vehicles, or a franchise tax. Indiana has these taxes, but the ad valorem tax has exemptions and the excise tax is fixed at a low amount (Jasek, Ojah, and Hoover, 2003). Another advantage some states provide is permanent truck and trailer plates rather than plates that are reissued annually. Online renewal options and “one-stop shops” for customer service were considered secondary criteria that might encourage trucking

companies to register with a particular state. Ohio has taken several steps to adopt some of these policies in order to become more competitive with other jurisdictions.

Perhaps the most interesting insight from the TTI study concerns apportionment. Any taxes or fees that are non-apportioned – meaning that in-state carriers must pay it but out-of-state competitors do not – are viewed by in-state carriers as placing them at a competitive disadvantage. This same logic compelled state officials to create the IRP agreement so that the highway maintenance costs (borne to repair damage caused by interstate truck traffic) could be shared more equitably. This is essentially the same conclusion drawn in the Kentucky Transportation Center’s (KTC’s) study of a fee-based alternative to its weight-distance tax. Eliminating the weight-distance tax and replacing it with a fee-based system would have apportioned costs less equitably, so that intrastate carriers would pay more while interstate carriers would, on balance, pay less (Martin, Bell, and Walton, 2013). Researchers and Ohio transportation officials plan to sidestep this issue by focusing on the reallocation of current revenues, and not on the imposition of new taxes and fees for in-state carriers.

IRP and the International Fuel Tax Agreement (IFTA) were created to apportion payments equitably to states and other jurisdictions. A recent study suggests that states are generally satisfied with the performance of the IFTA and IRP models, although some concerns about noncompliance and evasion have been voiced (O’Connell, Yusuf, and Hackbart, 2007). Notwithstanding past legal issues documented in the TTI study, most state officials believe the programs have been successful. These perceptions, however, have not precluded changes being made to the program’s structure. Specifically, IRP officials are now implementing a major change that was enacted in January 2015.

The change relates to the recently approved Full Reciprocity Plan: “a concept to change the International Registration Plan (Plan) to grant full reciprocity for all apportioned vehicles in all

member IRP jurisdictions, making the Plan more efficient to administer and more equitable and more flexible for its member jurisdictions and registrants” (IRP Task Force, 2010). Instead of granting reciprocity for jurisdictions in which organizations declare mileage, this system will let a carrier operate in all 59 jurisdictions if they comply with all other state and provincial laws. The change will streamline the registration process and simplify IRP program administration by eliminating estimated distance calculations, by reducing the need to obtain temporary (or trip) permits, and by decreasing the revenue associated with those two processes. Instead, first-year fees for new fleets will be collected and apportioned to all 59 jurisdictions, and subsequent filings will be based on the company’s actual logged miles (Sage, Casavant, and Lawson, 2013). However, the impact this change will have on IRP revenues is unclear. An independent study issued by the Freight Policy Transportation Institute suggests that the elimination of estimated distances and trip permits will be largely replaced because of the way mileage is recalculated and apportioned, with estimated losses and gains not exceeding four percent (Sage, Casavant, and Lawson, 2013). In practice, officials, researchers, and industry members are still unsure how the Full Reciprocity Plan will impact revenues or how the industry will respond to the new plan. Therefore, this change complicates the economic impact estimation for this study. In Ohio, any changes in the allocation of out-of-state apportionment fees will directly impact all counties and taxing districts.

Recent studies of Kentucky and Idaho’s commercial vehicle tax-and-fee structure show that the potential effects of fee-based commercial vehicle policies are difficult to forecast (Casavant and Jessup, 2004; Martin, Bell, and Walton, 2013). When officials replaced Idaho’s weight-distance tax with a fee-based system (following a 2001 court ruling), they did not anticipate the trucking industry’s response. Truck registrations declined sharply as trucking companies consolidated shipping routes to take advantage of a loophole capping the mileage-based fee. The

change was intended to be revenue-neutral, but Idaho now collects \$15-20 million a year less than it would have if its weight-distance tax was still in effect. Kentucky's weight-distance tax revenues have been much more stable and predictable than its IRP revenues. The latter fluctuate wildly due to the complex nature of jurisdiction funds netting, changes in plate fees, journal vouchers, and other economic factors. While Kentucky's weight-distance tax revenues tend to exhibit a strong positive correlation with highway usage and therefore the economic strength of the trucking industry, registration-based fees tend to weaken the relationship between highway use and user cost.

Competition from other states, uncertainty about the impact of the Full Reciprocity Plan, and potential volatility of IRP registrations could magnify the volatility of tax- and fee-based revenues garnered from commercial vehicle activities at the local level, particularly in Ohio. This KTC study will be critical for helping both Ohio and its constituent local governments assess the degree to which state and local policies are impacting its interstate truck registrations and for assessing the economic impact of losing registration fees.

Chapter 2. Ohio Motor Vehicle License Tax Distribution

The Ohio Department of Public Safety's Tax Distribution Section distributes vehicle license taxes – including the IRP taxes paid by commercial vehicles weighing over 26,000 pounds – to Ohio's counties, municipalities and, townships.² The distribution mechanism is very complex, as it involves registration fees from commercial vehicles registered in the state of Ohio, revenues from out-of-state carriers located in other Ohio jurisdictions, and the mechanism consists of several allocation formulas that push the license revenue to Ohio taxing districts.

When the state decided to join IRP, lawmakers and officials wanted to design a system that compensated counties and taxing districts for losses in registration revenue. Before joining IRP, counties and taxing districts received the entire apportionment of an Ohio license plate. Assuming the vehicle was registered for an entire year (i.e. not prorated), the entire plate cost was collected for the vehicle. When Ohio became an IRP jurisdiction, carriers began tracking mileage on each vehicle to determine how much of the apportionment should go to Ohio, instead of to other jurisdictions.

When Ohio entered IRP, officials decided that compensation for lost registration revenue on in-state plates would be offset by using the new revenue stream created from the remittance of apportioned registration dues from vehicles registered in other jurisdictions but operating in Ohio. Known as “loss compensation”, the revenue from carriers registered in other jurisdictions would be used to mitigate losses stemming from the apportionment of in-state IRP registrations. Since joining IRP, Ohio has collected enough revenue so that, even after providing all of the loss compensation for each Ohio-based vehicle, there is money remaining from the out-of-state funds

² IRP vehicles are generally defined in this document as an apportioned truck with a GVW over 26,000 lbs. However, the Plan includes other vehicles that are 26,000 GVW and under, as well as vehicles other than trucks.

at the end of each year. This money accumulates in a fund known as the IRP distribution fund. At the end of the year, once all Ohio-based IRP registration revenue and loss compensation revenue have been distributed, the remaining funds are distributed via Ohio's annual IRP excess compensation procedures.

Figure 1 is a flowchart that delineates Ohio's IRP tax distribution system. As the green box in the upper left-hand corner demonstrates, the initial revenue comes from Ohio-based carriers when they register or re-register a commercial vehicle. For each in-state registration, a \$30 fee is deducted and deposited in the Highway Safety Fund.³ Once that money is deducted, the remaining money is split between Ohio's Highway Operating Fund (the state's highway trust fund), the counties, and the taxing districts. If the vehicle is an IRP truck (i.e. its GVW > 26,000 pounds), the Highway Operating Fund receives 42.6 percent of the remaining license fee and the other 57.4 percent (the gross distributable license tax) goes to Ohio counties, municipalities and townships. Before money is disbursed, several things happen. Loss compensation must be calculated and added to the total.

As the second green box indicates, Ohio IRP license tax revenue is collected from other jurisdictions. It then moves through distribution steps similar to the in-state registration revenues before it eventually reaches the IRP distribution fund. The main difference is that rather than setting aside a specific amount for the Highway Safety fund, 2.5 percent of all out-of-state IRP revenues are transferred. The way IRP's Clearinghouse is set up, jurisdictions are only capable of tracking gross amounts from each jurisdiction. As such, Ohio officials do not see the amount of

³ According to ORC 4501.06, the Highway Safety Fund shall "be used for the purpose of enforcing and paying the expenses of administering the law relative to the registration and operation of motor vehicles on the public roads or highways. Amounts credited to the fund may also be used to pay the expenses of administering and enforcing the laws under which such fees were collected. All investment earnings of the state highway safety fund shall be credited to the fund."

Figure 1. Ohio IRP License Revenue Distribution Flowchart



revenue that is associated with each vehicle registered with another base jurisdiction. As with the Ohio-based IRP vehicles, 42.6 percent of the remaining out-of-state IRP revenue goes to the Highway Operating Fund, and 57.4 percent goes to the IRP distribution fund, which becomes part of the gross distributable license tax. This particular step is noted by the ① in Figure 1. The total amount of loss compensation depends on the weight class, percentage of logged miles run on Ohio roads, and the number of vehicles.

Table 1 illustrates how loss compensation works for a single truck in each of Ohio's weight classes. For example, the owners of an 80,000-pound truck registered in Ohio that logs 40 percent of its miles in Ohio would pay 40 percent of the full in-state fee, which is currently \$1,340. The Ohio portion of the bill is therefore only \$536; the remaining 60 percent of the vehicle mileage would be paid according to reported mileage and plate costs in other states in which the vehicle operated. For instance, if the truck accumulated 25 percent of its mileage in Kentucky, the carrier would pay 25 percent of a full Kentucky plate. This process would continue until all mileage was accounted for. When the truck's owners make their initial payment, it goes to Ohio's BMV. Once the BMV receives it, it distributes money due to other jurisdictions every month. Under this arrangement, carriers only have to pay a single state.

With an intrastate commercial truck, the amount sent to counties, townships and municipalities equals the amount remaining once the state's Highway Operating Fund share (42.6 percent) is deducted. Continuing with the example from the previous paragraph, assuming a full fee, this would have amounted to $(\$1,340) \times (0.426)$, or \$570.84. The remainder (\$769.16) is the raw amount distributable to the counties and taxing districts. However, the Highway Operating Fund share on an IRP truck with a 40 percent apportionment is \$228.34, with the remaining \$307.66 distributable to Ohio counties and taxing districts. Consequently, the shift to the IRP system would

create real losses in those counties and taxing districts where the vehicles are registered. To shield Ohio counties and taxing districts from large revenue declines under IRP, loss compensation was created.

Table 1. IRP License Fees and Loss Compensation by Weight Class

GVW	Full Year(\$)	Sans HSF (\$)	Collected (40%)(\$)	HOF(\$)	Gross(\$)	Loss Comp. (\$)	Total (\$)
26,001 - 30,000	385	355	142	60.49	81.51	122.26	203.77
30,001 - 34,000	450	420	168	71.57	96.43	144.65	241.08
34,001 - 38,000	510	480	192	81.79	110.21	165.31	275.52
38,001 - 42,000	570	540	216	92.02	123.98	185.98	309.96
42,001 - 46,000	630	600	240	102.24	137.76	206.64	344.40
46,001 - 50,000	690	660	264	112.46	151.54	227.30	378.84
50,001 - 54,000	755	725	290	123.54	166.46	249.69	416.15
54,001 - 58,000	815	785	314	133.76	180.24	270.35	450.59
58,001 - 62,000	885	855	342	145.69	196.31	294.46	490.77
62,001 - 66,000	955	925	370	157.62	212.38	318.57	530.95
66,001 - 70,000	1,025	995	398	169.55	228.45	342.68	571.13
70,001 - 74,000	1,110	1,080	432	184.03	247.97	371.95	619.92
74,001 - 78,000	1,230	1,200	480	204.48	275.52	413.28	688.80
78,001 - 80,000	1,370	1,340	536	228.34	307.66	461.50	769.16

Table 1 displays the IRP license plate fees and the first-pass calculation for commercial trucks registered in Ohio. The first column sorts vehicles according to weight class, and the acceptable range for vehicle plates. The second column contains the price for a 100 percent Ohio registration for a full year, but the \$30 reduction that goes to the Highway Safety Fund is deducted first. The collected amount is the total per vehicle based on apportionment, which is listed as “Collected (40%)” in the adjacent column. Next, the HOF fund represents the 42.6 percent distribution that goes to the Highway Operating Fund, whereas “Gross” is the gross distributable amount before loss compensation is included. The “Total” column is the distributable amount that goes to the county or taxing district as a result of the registration. It is identical to the distributable amount from an intrastate registration; the taxing district share that is left over after the Highway Safety

Fund and Highway Operating Road fund is deducted is identical to an IRP registration that is supplemented by the loss compensation.

Loss compensation is therefore determined by subtracting the distributable amount (i.e. the total amount going to Ohio's counties and taxing districts from the in-state registration) in the apportioned registration from the distributable amount in the full registration. For example, on an 80,000-pound vehicle that receives a plate with a 40 percent apportionment, there would be \$307.66 in gross distributable income rather than \$769.16, which would be the case if the truck were registered as an intrastate vehicle or an IRP vehicle that ran all of its miles in Ohio the previous year. If the apportioned amount is subtracted from the full amount, what remains is the loss compensation amount – \$461.50. This is the amount of money that comes from the out-of-state transmittals for trucks registered in other jurisdictions and operating in Ohio. As a result, there is still \$769.16 in distributable revenue – but only \$307.66 comes from the Ohio carrier.

The second major step is the distribution formula, which is denoted as ② on

Figure 1. According to O.R.C. Section 4501.04, the revenue must be distributed as follows: 34 percent goes to the county or municipality the vehicle is registered in; 47 percent goes to the county the vehicle is registered in; 9 percent is totaled statewide and then distributed to all counties based on each county's proportion of total road miles; 5 percent is totaled statewide and then distributed to all townships based on the proportion of each township's road mileage; and 5 percent is divided evenly between each of Ohio's 88 counties. Table 2 displays the approximate distribution ratios for each vehicle based on weight class. Because the loss compensation equalizes the amount of distributable revenue per vehicle, the apportionment does not matter in terms of this

distribution, although it impacts the amount drawn from the IRP distribution fund to cover the distributable revenue portion that does not come from the Ohio carrier.

Table 2. Breakdown of Ohio IRP Distributable Revenue per Vehicle, GVW

GVW	Total Non-HOF	Muni/Township (34%)(\$)	County (47%)(\$)	County Miles (9%)(\$)	Township Miles (5%)(\$)	County Even (5%)(\$)
26,001-30,000	203.77	69.28	95.77	18.34	10.19	10.19
30,001-34,000	241.08	81.97	113.31	21.70	12.05	12.05
34,001-38,000	275.52	93.68	129.49	24.80	13.78	13.78
38,001-42,000	309.96	105.39	145.68	27.90	15.50	15.50
42,000-46,000	344.40	117.10	161.87	31.00	17.22	17.22
46,001-50,000	378.84	128.81	178.05	34.10	18.94	18.94
50,001-54,000	416.15	141.49	195.59	37.45	20.81	20.81
54,001-58,000	450.59	153.20	211.78	40.55	22.53	22.53
58,001-62,000	490.77	166.86	230.66	44.17	24.54	24.54
62,001-66,000	530.95	180.52	249.55	47.79	26.55	26.55
66,001-70,000	571.13	194.18	268.43	51.40	28.56	28.56
70,001-74,000	619.92	210.77	291.36	55.79	31.00	31.00
74,001-78,000	688.80	234.19	323.74	61.99	34.44	34.44
78,001-80,000	769.16	261.51	361.51	69.22	38.46	38.46

In each weight class, the distribution formula is basically the same. The 34 percent municipal/township distribution is returned to the municipality if the truck is registered in an Ohio city or village. However, if it is registered in a township the money goes to the county. Therefore, counties with a large percentage of township registrations generally receive more revenue per vehicle, all else being equal, than counties with a large proportion of municipal registrations. The 47 percent distribution always goes to the county, and as shown in Table 2, this is the largest amount.

Table 3 provides a hypothetical breakdown of the IRP license for a truck registering for a full year, based in a township of Adams County. Of the \$769.16 in distributable revenue for the 78,001 pounds and up plate, \$361.51 goes directly to the county. The 34 percent city or township distribution goes to the municipality if the vehicle is based there. If the vehicle is based in a township, this money goes to the county. The remaining pools of money go to a statewide pool

that combines all license revenue based on all vehicle registrations — not just IRP vehicles. The county mileage and township mileage money is summed statewide and then distributed based on statewide mileage percentages. The county’s even (5%) amount is also technically distributed in this way. The initial calculation determines the amount of distributable revenue for each registration in each county and taxing district. The distribution is how much the county or township keeps after all of the calculations have been made.⁴

Table 3. Hypothetical Ohio IRP Registration and Tax Distribution (Adams County)^{##}

Distribution	%	Amount (\$)	To Adams County (\$)	To Other Counties/TDs (\$)
City/Township	34	261.51	*261.51	0.00
County	47	361.51	361.51	0.00
County Miles	9	69.22	0.90	68.32
Township Miles	5	38.46	**0.35	38.11
County Even	5	38.46	0.44	38.02
Total	100	769.16	#624.71	144.45

*If it is a township registration, the 34 percent goes to Adams County, and to the city otherwise

**This money passes through Adams County but ultimately goes to its townships

#Adams County keeps \$624.36 after deducting the township money

##Figures shown do not reflect cost or interest

The county mileage share (9%) is divided based on each county’s proportion of all county road miles in the state. In this example, the truck is registered in Adams County, which has 375.81 of the statewide total (28,976.38 county miles). Dividing the county road miles in Adams County miles by the total number of county miles in Ohio yields 0.013. This means that 1.3 percent of all money in the county mileage pool is apportioned to Adams County. Using an 80,000-pound truck as an example would mean that approximately 90 cents of the \$69.22 of that particular vehicle’s county mileage distribution go to Adams County irrespective of what county it was registered in.

The same logic can be applied to township mileage. Adams County has 15 townships, with 383.95 township miles – just under 1 percent (.009) of the state’s 41,497.3 aggregate township

⁴ This does not apply to municipalities, who are only eligible to receive 34 percent of the license distribution for each vehicle registered within its boundaries.

miles in 2013. As such, for a single 80,000-pound truck registration, assuming it is not prorated, approximately 34.6 cents from each registration goes to Adams County based on its share of statewide township mileage, regardless of where in Ohio the vehicle is registered. It could be in Adams County, another county, or even a municipality in another county. All other counties would receive allocations for its townships based on their number of township miles (which is used to calculate the proportion of statewide township miles that fall within their borders). The initial distribution is transferred from the Ohio Department of Public Safety to the counties, which then allocates each township its share.

The last distribution is less complicated. Basically, the 5 percent county distribution is divided evenly between the 88 counties. Continuing the example of an 80,000-pound truck, Adams County would get about 44 cents of the \$38.46 amount, as would each of the 87 other counties in the state. This would apply to every IRP truck in the state that was registered for the 78,001-pound-and-up plate.

In sum, if the hypothetical vehicle were registered in an Adams County township, the county would receive \$261.51 from the city/township share, \$361.51 from the county share, 90 cents from the county mileage share, and 44 cents from the county even share. Adams County's 15 townships would split the 35 cents it collected based on those townships' mileage share. The remaining money acquired from the county mileage, township mileage, and county even shares would be distributed to each of the other 87 counties accordingly. As such, the vehicle registered in Adams County would result in \$769.16 cents in distributable revenue, but Adams County would only keep \$624.36 of that registration. When the additional factors of prorated registrations, BMV costs, and interests are taken into account, the total amount Adams County retains averages less than \$624.36

per 80,000-pound truck registered in a township, illustrating the tax distribution process's complexity.

The last phase of the IRP tax distribution process, which is marked with the ③ in Figure 1, concerns the handling of the remaining out-of-state revenue received from other jurisdictions. At the end of each calendar year, the ODPS Tax Distribution Section determines the amount of out-of-state revenue left over after loss compensation, interests, and other adjustments are made from the out-of-state IRP revenue generated from vehicles registered in other base jurisdictions. This amount varies from year to year, but since Ohio joined IRP there have always been leftover out-of-state IRP funds after loss compensation, interest, and other adjustments. Table 4 summarizes the statewide annual excess IRP compensation distribution for Ohio since 2009. The revenues have averaged \$9.6 million over the last six years, and ODPS distributed them to Ohio's 88 counties in a manner similar to the distribution of in-state registrations and loss compensation.

Table 4. Ohio Statewide Annual Excess IRP Compensation Distribution

Year	Total (\$)
2009	9,930,742.72
2010	9,310,356.89
2011	8,545,913.47
2012	9,494,625.38
2013	10,682,385.59
2014	9,788,898.74

To distribute the annual excess loss compensation, the ODPS Tax Distribution Section calculates the total amount of license revenue that each county and taxing district received in the past year's monthly license tax distribution. This total includes all forms of license revenue – IRP trucks, non-IRP commercial trucks, passenger vehicles, buses, and motorcycles, among others.

The annual excess loss compensation amount is divided up in the same proportion as the motor vehicle tax distributed in the last year, undergoes the 34/47/9/5/5 calculation, and then final calculations to determine the amount each county and taxing district will receive.

For 2014, approximately \$9.79 million was distributed in annual excess compensation along with \$304.62 million in total license tax. The ratio of excess annual distribution to overall license tax is 0.032. This is the excess compensation ratio (ECR). A key difference between the license tax and loss compensation distribution versus annual excess distribution is that the latter is calculated using all vehicle license tax as the basis for the ratios. To determine each county's initial share of the annual excess compensation, the ECR ratio is applied to the total license revenue for all Ohio counties. For example, Vinton County and Vinton County's taxing districts received \$849,650.69 in license revenue. To arrive at Vinton County's portion of the \$9.79 million annual excess compensation revenue, \$849,650.69 is multiplied by the ECR, which is \$27,303.74.

Table 5. Annual Excess Compensation for Vinton County, 2014

Category	%	Amount to be Distributed (\$)	Amount Retained (\$)
Muni/Township	34%	9,283.26	*8,999.60
County	47%	12,832.76	12,832.76
County Miles	9%	2,457.34	6,045.97
Township Miles	5%	1,365.19	#0.00
Counties Evenly	5%	1,365.19	5,561.88
Total	100%	27,303.74	33,440.21

Table 5 extends this example by summarizing the breakdown of annual excess compensation revenue that Vinton County received for the 2014 calendar year. Here the 34/47/9/5/5 calculation and distribution are accounted for. The original amount to be distributed based on the ECR ratio is noted in the second column. Vinton County, according to the calculation, received \$9,283.26

for the municipality/township share of the registrations, \$12,832.76 for the county share of the registrations, \$2,457.34 for the county mileage, \$1,365.19 for the township mileage, and \$1,365.19 for the even county split. What the county actually retained after the distribution looks quite different. Specifically, for the municipality/township portion of the registration revenue, only the township revenue remains with the county – the municipality gets the rest. This amount is calculated by identifying the proportion of city and township revenue and multiplying each by 34 percent. This number is then multiplied by the ECR.⁵ This indicates that Vinton County kept \$8,999.60.

Counties always retain the 47 percent amount of the calculation after the 34/47/9/5/5 distribution. In this case, Vinton initially received and retained \$12,832.76 after the ECR and county mileage apportionment were applied to the annual excess distribution fund. The county mileage apportionment works quite differently, however. Vinton County's calculated amount of the money for its county road mileage was \$2,457.34, a figure derived from multiplying the ECR times the county's total vehicle license tax receipts times the 9 percent distribution amount. In fact, the initial \$2,457.34 was divided among Ohio's 88 counties based on their respective proportion of total county road miles. Vinton County currently has 0.7 percent of all county road miles in the state.⁶ Thus, Vinton County retained 0.7 percent of the \$2,457.34 – or \$17.20. However, Vinton County also received 0.7 percent of the county road mileage calculation for each county – \$6,045.97 once it was distributed.

None of the township mileage money from the annual excess compensation fund ultimately stays with the county; it is distributed in a manner similar to the county mileage. Vinton County's initial calculated amount of its township mileage was \$1,365.19 (calculated by multiplying the

⁵ The township and municipality splits for Vinton County are not included.

⁶ Based on ODPS mileage reports from 2013.

ECR times the total county's vehicle license tax receipts times the 5 percent distribution amount). As with the county mileage, this distributed amount is redistributed based on the proportion of state township mileage located in each county. In the case of townships, Vinton County's mileage proportion is 0.77 percent. Only \$10.92 of the township share went to Vinton County's townships, but as with the county mileage share, Vinton county's townships received 0.77 percent of this amount from the other 87 counties, making the total redistributed township mileage share \$3,762.90. Vinton County townships would share this money based on the total number of miles located in each township, but that breakdown goes beyond the scope of this study.

Lastly, the remaining 5 percent of the excess annual compensation is distributed to Ohio counties evenly. The simplest way to conceptualize this distribution is not to use the ECR but to multiply the total excess annual compensation amount by 5 percent and then divide by 88. In 2014, this equation would be $\frac{\$9,788,898.74 * .05}{88} = \$5,561.88$.

If all of these redistributions are added together, Vinton County's retained total (as opposed to the initial distribution total) from the annual excess compensation distribution for calendar year 2014 came to \$33,440.21, with an additional \$3,762.90 going to its townships. This was in addition to the \$117,494 Vinton County retained for based on its IRP registrations and loss compensation (after redistribution), as well as the \$19,426 passed along to its townships. In total, 2014 IRP registrations netted Vinton County \$150,934, and its townships received \$23,189. These calculations are performed for each county and taxing district by the ODPS Tax Distribution Section.

The vehicle-level and county-level assessments of the Ohio IRP vehicle registration serve as micro-level illustrations of macro-level tax distribution policies. These examples illuminate the distribution mechanisms inherent to the system and clarify how we arrived at statewide totals for

Ohio IRP taxes. Table 6 displays the statewide Ohio IRP distribution numbers, 2009–2014. The first column lists the calendar year. The second reports the distributable amount for the IRP license tax collected from Ohio trucks based on each vehicle’s in-state apportionment. The HSF and HOF deductions have already been made. The next column summarizes the loss compensation amount. The fourth column has the total amount that was actually distributed from in-state registrations and loss compensation after removing costs and interests, and therefore the total is slightly less than if the second and third columns were simply added together. The distribution amounts encompass what goes to counties, townships and municipalities. The fifth column contains the IRP excess distribution, which includes leftover IRP loss compensation funds after all of distributions to taxing districts, administrative costs, and interests have been taken into account.

Table 6. Statewide Ohio IRP License Tax Distribution, 2009-2014

Year	Ohio IRP (\$)	Loss Comp (\$)	Distributed (\$)	IRP Excess (\$)	Dist. + Excess (\$)
2009	\$20,930,496	\$25,694,032	\$41,978,599	\$9,930,743	\$51,909,342
2010	\$21,003,028	\$27,074,290	\$43,319,618	\$9,310,357	\$52,629,975
2011	\$21,780,550	\$28,934,120	\$46,003,101	\$8,545,913	\$54,549,014
2012	\$22,350,550	\$29,814,617	\$47,434,570	\$9,494,625	\$56,929,195
2013	\$22,077,017	\$30,375,930	\$47,358,198	\$10,682,386	\$58,040,584
2014	\$23,828,117	\$32,216,767	\$50,535,487	\$9,788,899	\$60,324,386

The data in Table 6 begin in 2009 and run through 2014. The total distributed amount shows a year-over-year increase for the entire period. This time period aligns with the economic recovery that followed the Great Recession. Economic growth is generally a good predictor of increased revenue from taxes and fees, other factors notwithstanding. The average annual distributable amount (excluding IRP excess) during this period was \$51,013,252. The IRP excess fluctuated from year to year, but deviated little from the \$9,625,487 average. When the monthly distribution and excess distribution are both taken into account, there was steady growth in the amount of IRP revenue received by Ohio counties and taxing districts.

Figure 2 displays the estimated IRP distribution kept by each county for 2014. The total comprises the adjusted distribution amount, which takes the initial 34/47/9/5/5 calculations and distributions into account. Only funds that counties actually get to keep are included in these totals. Annual excess compensation is not included. The totals exclude the share of funds going to municipalities, which receive the 34 percent share. As previously noted, counties keep the 34 percent share if the vehicle is registered in a township, so that amount is included. The 5 percent distribution by township miles goes to the townships, so it is not included. The figure is color-coded by revenue category.

Estimated totals show significant variability, from \$98,622 in Morgan County to \$2,902,108 in Franklin County. Unsurprisingly, most of the top recipients are the most populous counties in Ohio, with the three most populous counties (Cuyahoga, Franklin, and Hamilton) among the top five in terms of retained revenue. In some cases, this differs significantly from the initial distribution. Counties with a large proportion of their registration in municipalities lose the 34 percent distribution they would have otherwise received had the trucks been registered in townships. Spatial distributions of county totals are strongly related to the location of Interstate routes throughout Ohio. Interstates 74 and 75 in Southwest Ohio; Interstates 70 and 71 in the Columbus area; and Interstates 77, 76, 80, and 90 in Northeast Ohio all pass through counties with higher volumes of trucking activities. Counties that are ports-of-entry also tend to collect more trucking registration revenue than the state's interior counties.

Figure 2. Estimated IRP License Distribution Kept by County, 2014

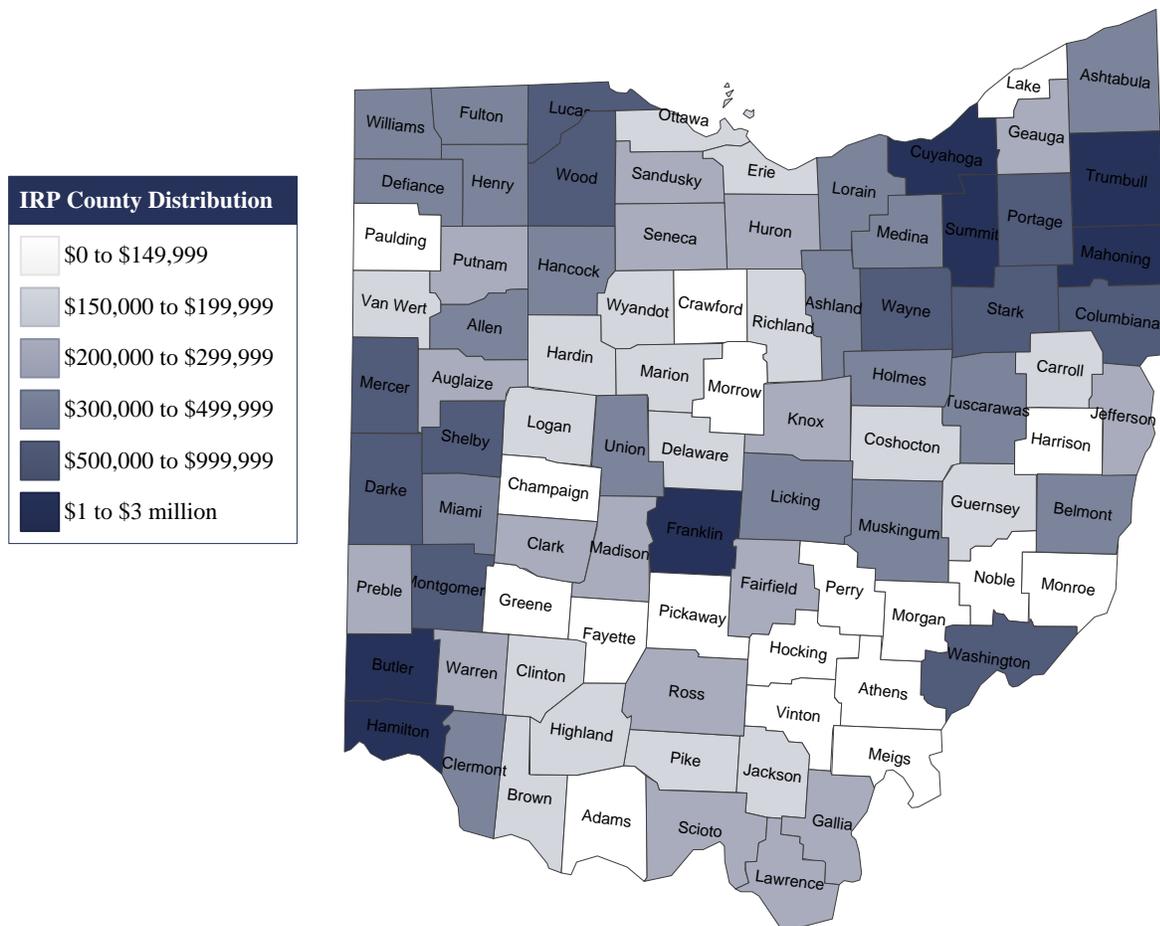


Figure 3 displays the total IRP annual excess compensation kept by each county after remaining out-of-state IRP funds were collected, calculations completed and distributed according to the 34/47/9/5/5 ratio. The key difference is that each county’s initial allocation from the excess compensation fund is based on a ratio of its share of all motor vehicle license tax, not just the IRP component. In 2014, Ohio distributed over \$304 million in vehicle license taxes from passenger vehicles, motor homes, motorcycles, house vehicles, mopeds, commercial and non-commercial trailers, non-commercial trucks, farm trucks, buses, non-IRP trucks and IRP trucks. The ECR was calculated by dividing the annual excess fund (≈ \$9.79 million) by the \$304 million total. In 2014,

the ECR was ≈ 0.032 . The ECR was applied to each county's total motor vehicle license revenue to determine totals allocations for individual counties. For example, Cuyahoga County and the taxing districts within the county received \$20.7 million in license revenue in 2014, which multiplied by 0.032 comes to about \$665,772. This money then undergoes the 34/47/9/5/5 calculation.

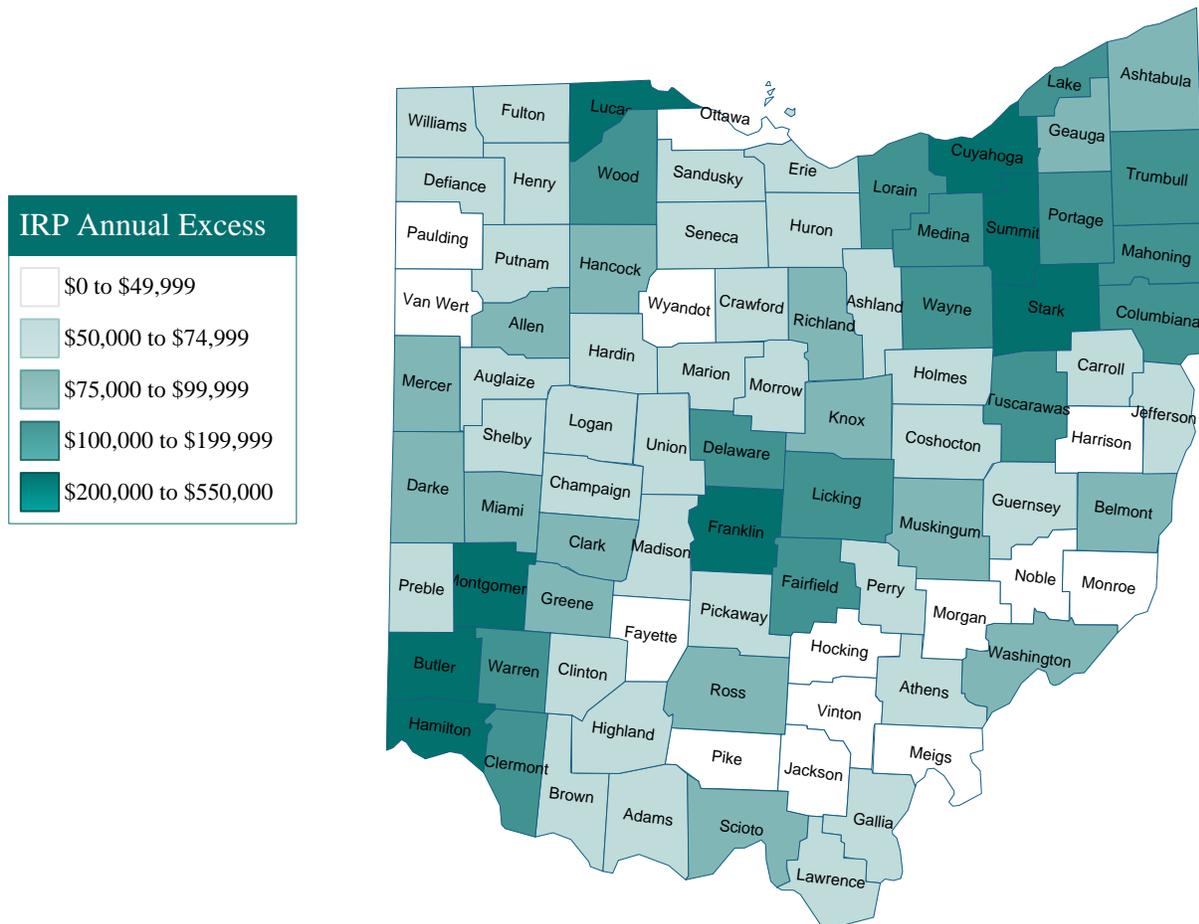
As Figure 3 indicates, none of the counties retained more than \$550,000 of the annual excess compensation. How can we explain Cuyahoga County's totals in light of this knowledge? The answer is that some of the \$665,772 is diverted to other taxing districts, as was the case with the Vinton County example. The largest recipients of distributable county revenue and loss compensation are similar to the largest recipients of annual excess compensation. The correlation coefficient for the two amounts is .910.⁷ In a few cases divergence emerges if there is a county with a large amount of IRP truck revenue but a relatively small amount of overall license revenue, or a small amount of IRP truck revenue and a large amount overall license revenue. Counties with stark distributions of commercial and residential areas in municipalities and townships may also observe such a divergence, though it is not common.

Although complex, Ohio's system of motor vehicle license tax distribution was designed as a compromise between state and local entities. All of these stakeholders demand resources to maintain and improve roads and related infrastructure. The allocation formulas for distributable income were designed to provide money to counties, municipalities and townships. In most cases, the system works well because vehicle registrations are not generally a fungible obligation. Individuals who attempt to avoid paying the vehicle license tax risk being stopped and fined by

⁷ Correlation statistics measures the strength and direction of a linear relationship between two variables, which in this case are 1. distributable county revenue plus loss compensation, and 2. annual excess compensation.

law enforcement, even those who purchase a vehicle in another state in an effort to evade their home state's tax.

Figure 3. Estimated IRP Excess Annual Distribution Kept by County, 2014



However, IRP rules give trucking companies significant flexibility over where they register commercial vehicles, particularly if they have terminals in multiple states. Carriers often choose the state with the most lucrative tax policies and register vehicles there, even if they do not intend to maintain significant operations in that state. This practice, coupled with Ohio's motor vehicle tax distribution policy changes the IRP revenue allocation, and in many instances localities lose

funding as a result. The next section discusses IRP registration issues and their impact on license revenue distribution in Ohio.

Chapter 3. Ohio IRP Registration Issues

After understanding the complex mechanics Ohio's IRP tax distribution process, it is easier to anticipate how changes in motor carrier registration patterns affect taxing districts across the state. The registered location of Ohio's commercial vehicle is of paramount importance, because the registration is what anchors the IRP revenue to Ohio counties and taxing districts. Per county, this is particularly important given that most of the IRP funds go to the counties for roadway improvement and maintenance purposes. When trucking companies engage in jurisdiction shopping to reduce their tax burden – that is, to reduce taxes other than IRP taxes – it changes the IRP tax distribution mechanisms in ways detrimental to Ohio's taxing districts. If the company continues to domicile most or all of its vehicles in the taxing district that previously received its IRP revenue, but now registers those vehicles in another state to save money, the community loses many of resources historically allocated to assist with highway infrastructure improvement and maintenance.

Economic development initiatives may encourage multistate companies to move headquarters or to register vehicles in another state, and the company benefits from providing incentives or exemptions for taxable assets. Technically, it is not the avoidance of IRP fees that save a company money, but the avoidance of other taxes a company pays because it has assets in a particular state. If a company registered in Ohio moves a registration to Indiana but still runs the same proportion of its total miles in Ohio, the amount remitted to Ohio remains largely unchanged. As noted in the introduction, the taxes, fees, administrative costs, customer service, licensing requirements,

regulations, IRP registration payment options, and other policies tied to a registration typically have a more decisive effect. When a county, municipality, or township loses a registration because the vehicle is registered in another state, but still operates in Ohio, the state still receives the same amount of money, assuming the proportion of miles, registered weight class, and registration duration (i.e. no proration) stay the same.

However, instead of putting money in the in-state pool for distribution to its taxing district, all of the funds are shifted to Ohio's IRP distribution fund. These funds are then used to supplement remaining in-state registrations or are allocated as part of the annual excess compensation distribution. This is based on a percentage of all motor vehicle license revenue, not just IRP license revenue. Consequently, if a county loses a significant number of IRP registrations due to jurisdiction shopping, revenue may still go to the state through interjurisdictional funds netting and through direct payment from jurisdictions not participating in the IRP Clearinghouse, but the revenue is not distributed in the same manner. The effects are difficult to project because of a multitude of other factors related to IRP revenue distribution in Ohio.

Conceptually, the problem is easily defined. However, addressing it is an entirely different matter. IRP allows carriers to register in any jurisdiction where they meet the base residency requirements. According to IRP, Inc., the base jurisdiction "is where the motor carrier has an established place of business and owns, leases or rents a physical structure that is designated by a street name or road"⁸ (IRP, 2015).⁸ There are several methods carriers can use to prove their base jurisdiction residency, including: utility bills with the owner(s) or company's name and address, state government documents showing corporate residency, a weapons permit, bank statements, a

⁸ IRP, Inc. 2012. "IRP Frequently Asked Questions." Retrieved 15 April 2015 at: <http://www.irponline.org/?page=EDUFAQ#23>.

driver's license, titles, tax returns with the home jurisdiction in the return address, and a health care card (in Canadian provinces only).

It is possible for carriers to illegitimately claim residency in a jurisdiction by fraudulently manipulating these documents to demonstrate residency where none exists. However, legitimate jurisdiction shopping can also occur, whether a carrier moves its terminal to another jurisdiction or expands to a jurisdiction with more favorable policies. The former is something IRP members have tried to address, but the latter is more difficult to remedy. Carriers engaged in jurisdiction shopping are more likely to be larger companies because they have the resources necessary to study and understand the system so it can be exploited to their advantage. With the constant flux of registrations within jurisdictions and across jurisdictions, economic boom-and-bust business cycles, businesses changing ownership, registrants changing USDOT numbers, and data limitations, gauging the extent to which jurisdiction shopping occurs can be difficult.

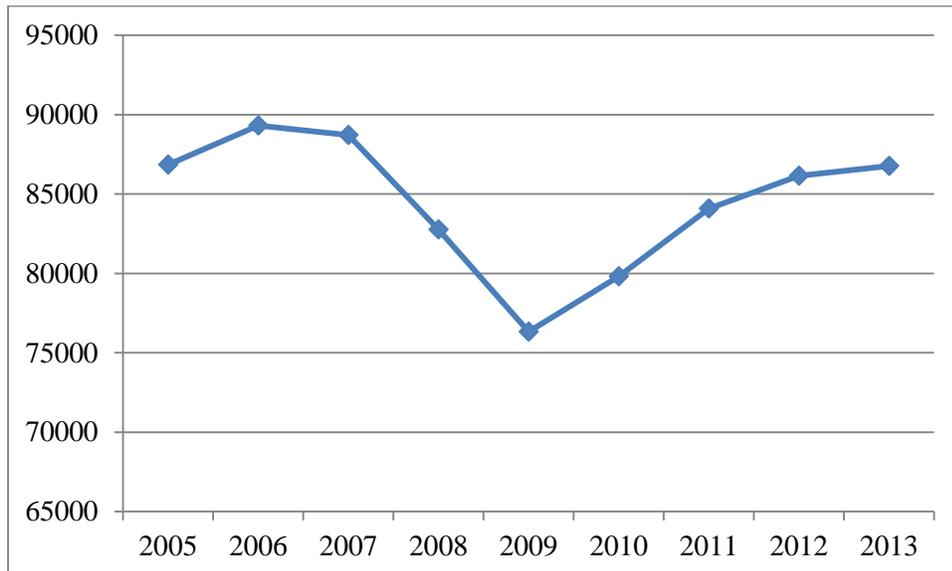
There are several ways to assess the impact of jurisdiction shopping on Ohio counties. The first method is to evaluate the difference in registration numbers or registration share over time to identify if certain counties are trending downward. The second method is matching IRP vehicles plated in other states to trucking companies in Ohio by based on USDOT numbers, in which identifiers are tied to individual vehicles and the Ohio companies. Third, an analysis of IRP registration revenue trends in Ohio's 88 counties could provide clues about whether the changing dynamic of revenue is related to registration trends. A final strategy is to look at known instances of jurisdiction shopping and determine its effect in particular Ohio counties.

3.1 Registration Trends

Following the 2009 recession, Ohio's IRP truck registration numbers declined significantly before rebounding. Figure 4 displays the registration totals from 2005 through 2014. In-state IRP

registrations peaked in 2006 at 89,307 before falling slightly in 2007 and then dropping sharply through 2008 and 2009. Registration numbers have since rebounded, reaching 86,766 in 2013, which falls just short of 2006 levels. For county-specific analysis, 2009 is the optimal starting point because the economy had reached its bottom. As such, isolating specific counties where jurisdiction shopping is most prevalent is a more straightforward procedure. Registration drops could still be related to economic issues or normal patterns of business termination, but these factors are more prevalent during recessions than during recoveries.

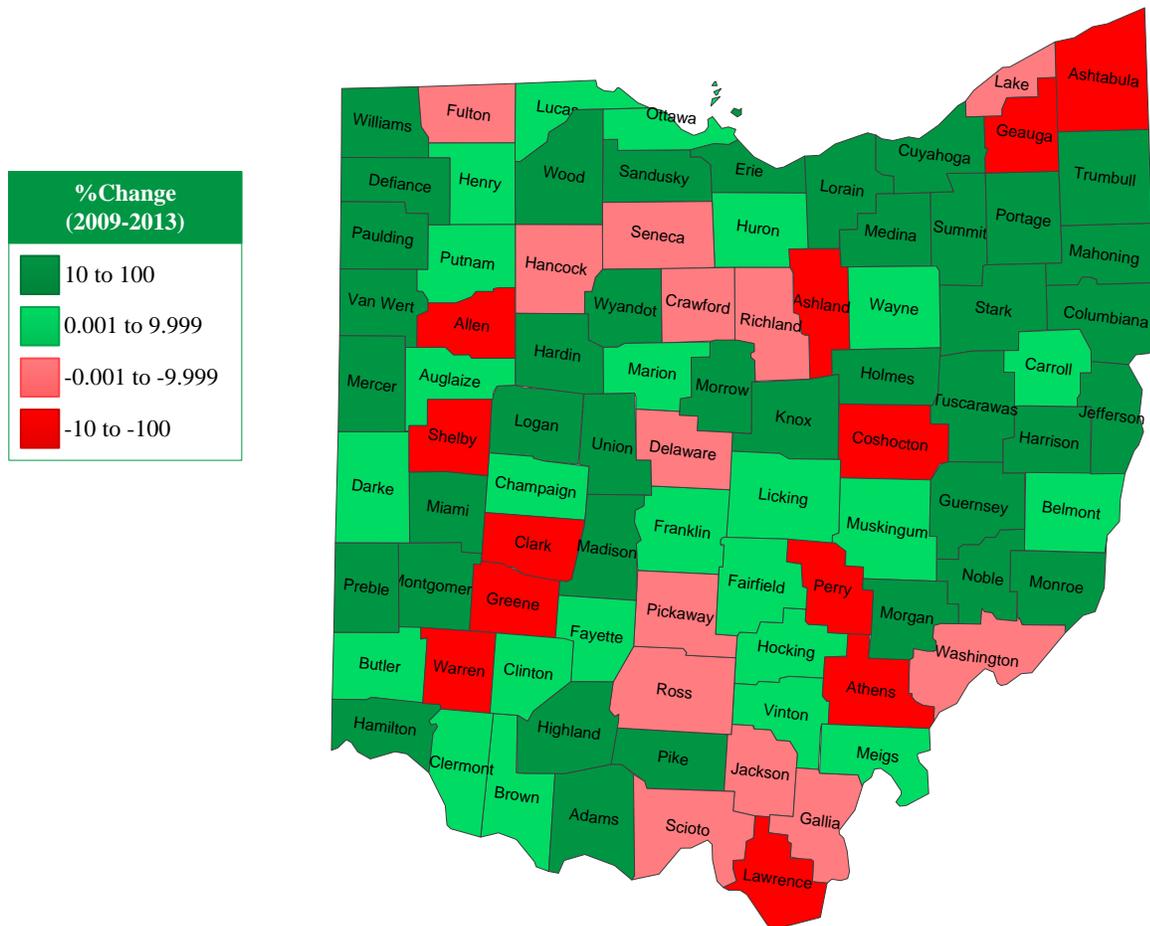
Figure 4. Ohio IRP Truck Registrations, 2005-2013



IRP registrations might fluctuate significantly within a county for internal and external reasons. Economic performance and development, shifts in industrial production and product distribution, population changes, or trucking company startups and closings may drive these numbers — and they have little to do with jurisdiction shopping. Given that most of the data correspond to a period of general economic expansion, a negative trend might raise flags. There are several ways to temporally analyze the registration activity to identify clues about which areas are most vulnerable to jurisdiction shopping might. The first is to compare the change in registration percentage over

time. Figure 5 shows the percent change in registration percentage between 2009 and 2013 (data were not available for 2005 to 2008). All counties show either positive or negative trends (none remained unchanged). Counties with positive trends are indicated in green, and counties with negative trends are indicated in red. Shading indicates the magnitude of change. For example, as the positive change in registration becomes more pronounced, it is indicated with a darker shade of green (the same logic applies to registration declines and the corresponding red shading).

Figure 5. Ohio IRP Registration Change, 2009-2013



Between 2009 and 2013, total IRP registrations rose from 76,334 to 86,766, an increase of 13.7 percent. Therefore, registrations increased in 63 counties but decreased in 25 counties. The

percent increase was quite sizable in several instances, with 39 counties showing at least a 10 percent increase. Conversely, only 12 counties suffered a decline of 10 percent during the study period. The other 37 counties saw registration increases or decreases within 10 percent of their 2009 numbers. The counties to scrutinize are those that had large IRP disbursements in 2014 (see Figure 3) but which also had registration decreases preceding those disbursements. These counties – Lake, Geauga, Ashtabula, Columbiana, Scioto, Delaware, and Warren Counties – are where we would anticipate sizable revenue losses. As such, they may be good candidates for investigation of prevalent jurisdiction shopping activities.⁹

Another factor to consider is patterns of IRP registration terminations. Under this scenario, a trucking company eliminates all of its IRP registrations in Ohio. To determine the number of companies fitting this profile, we took Ohio’s IRP vehicle data and calculated the number of trucks registered by each company (or unique USDOT number) in the state from 2009 to 2013. Only a 100 percent year-to-year fleet reduction counted as a termination. Additionally, if a trucking company re-registered vehicles after a year or suspended operations they were not counted. After starting with 12,099 companies listed in the vehicle data for 2009-2013, this approach whittled the number of down to 3,905 – roughly a quarter of the companies registered in Ohio during those years.¹⁰ Lapsed IRP vehicle registrations totaled 10,250.

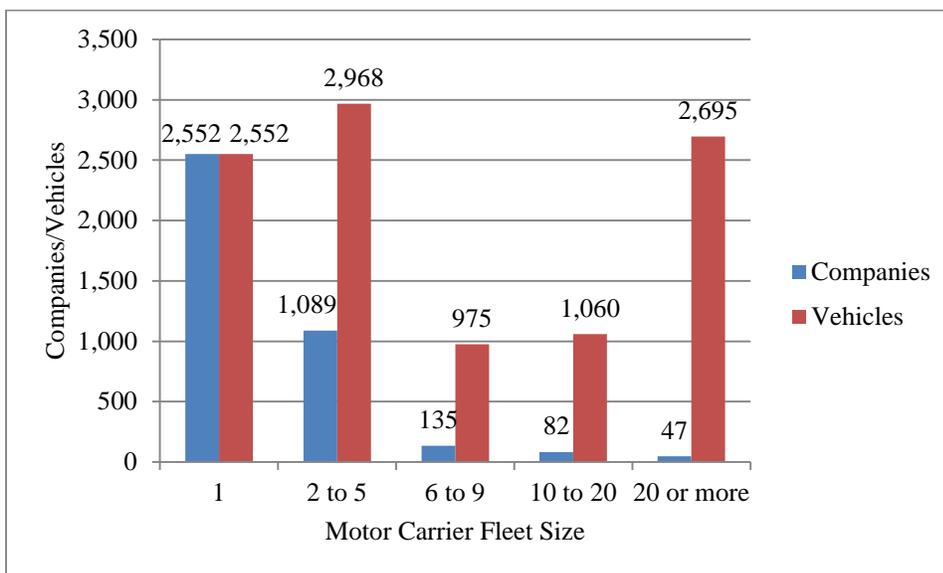
Figure 6 shows the distribution of IRP companies that stopped registering all their vehicles in Ohio during the 2009–2013 interval as well as the total number of vehicles no longer registered. Classification was based on a company’s total number of Ohio registrations: one vehicle, 2 to 5 vehicles, 6 to 9 vehicles, 10 to 20 vehicles, and 20 or more vehicles. As the data for Group 1

⁹ Revenue trends will be addressed in Section 3.2.

¹⁰ The Xerox vehicle data and BMV registration data do have some discrepancies, so the vehicle totals are not the same.

indicate, 2,552 of these companies were single-truck operations. Despite these owner-operators' large numbers, these companies accounted for just under a quarter of all the vehicles whose IRP registrations were discontinued. There were 1,089 companies with 2,968 vehicles in the 2 to 5 grouping; they both comprised just under 30 percent of all companies and vehicles. In the 6 to 9 range were 135 organizations and 975 registrations. While the 10 to 20 and 20 or more categories only accounted for 3.3 percent of these organizations, they comprise 36.6 percent of all the registrations.

Figure 6. Companies and Vehicles with Lapsed IRP Registrations in Ohio, 2009-2013



These registration terminations could stem from three causes: (1) the company is no longer in operation; (2) the company relocated its registrations (and possibly its operations) to another jurisdiction; or (3) the company continues to operate in Ohio but did not resume operations until 2014 or later. To determine the frequency of each scenario, the USDOT numbers of vehicles with terminating Ohio IRP fleet registrations were matched to IRP's current database of vehicles to identify states where a carrier still had registered vehicles.

Error! Not a valid bookmark self-reference. Table 7 summarizes data on Ohio fleet cancellations. It includes the current status of the terminating companies as well as the total number of vehicles that had registrations cancelled between 2009 and 2013. The rightmost column reports the number of vehicles currently associated with any company that has reactivated operations in Ohio or continued them in other jurisdictions. The vast majority (3,308) of the companies no longer operate as interstate trucking companies, although it is possible some of these continued operations as intrastate companies. Consequently, no currently registered IRP vehicles are associated with these companies. These companies terminated 7,947 registrations between 2009 and 2013. 131 of these companies have since reregistered 448 vehicles and recommenced operations after cancelling 362 registrations between 2009 and 2013. A glance at the year-to-year registration records of Ohio's IRP carriers shows that deregistration, a year of no operations, and re-registration in a subsequent year is not uncommon, particularly with smaller companies. We identified 466 companies that no longer register IRP vehicles in Ohio that are still active in other jurisdictions. They cancelled 1,941 vehicles in Ohio, and no longer register any vehicles in the state. Currently, they have 101,905 registrations active in other IRP jurisdictions. Most of these companies are multistate carriers with large regional or national operations.

Table 7. Ohio Fleet Cancellations by Company and Vehicle Numbers, 2009-2013

Status	Companies	Cancelled Registrations	Current Registrations
No longer operating	3,308	7,947	-
Have current Ohio operations	131	362	448
Active in other jurisdictions	466	1,941	101,457
Total	3,905	10,250	101,905

The last category includes companies that have taken one of three paths. First, it is possible these companies halted operations in Ohio but continued them in other states. It is also possible

these companies continued operating in Ohio but no longer registered vehicles there. Last, it is possible that gaps in data (i.e. the fact that the historical Ohio data ends in 2013) will ultimately show how a company shifted its primary location but still registers some vehicles in Ohio. The fluid nature of IRP registrations and trucking company operations makes it difficult to pin down the number of vehicles involved. The 466 companies terminating 1,941 vehicles during their last year of registration had a total 2,763 vehicles during the 2009 to 2013 period, which means the companies eliminated some vehicles in previous years before terminating the remainder of their fleet. A match process for these 2,763 vehicles shows that 1,808 of these vehicles are still active, including 375 in Ohio. Thus, 375 vehicles belong to out-of-state companies that once had fleets in Ohio but cancelled registrations, moved operations elsewhere, and then re-registered some of the same vehicles with the state. The remaining 1,433 vehicles were registered in Ohio at one time but are now registered in another state. These vehicles represent possible instances of jurisdiction shopping.

Based on conversations with Ohio officials about jurisdiction shopping, the 1,433 potential IRP vehicles registered elsewhere but potentially operating in Ohio is lower than expected. Because this practice has been in effect for several years, many vehicles never show up as having been registered in Ohio. For example, Greenwood Motor Lines, which does business as R & L Trucking, is a large carrier based in Wilmington, OH that has registered its vehicles in Indiana since 2008. Their Ohio registrations moved from the state before the historical data began. Another possibility is that Ohio-based companies deregister some – but not all – of their fleet. The matching criteria should therefore be relaxed.

The most straightforward approach is to match IRP vehicles registered in other states to any Ohio-based carriers. To do this, the IRP vehicles were matched to a database of the current primary

address for Ohio motor carriers based on corresponding USDOT numbers. The results of the matching process identified 20,601 vehicles associated with 769 carriers. The state-by-state breakdown is provided in Figure 7. As the map shows, there are out-of-state registrations in most U.S. states, although the trend is more prevalent in some states than others. There were no such registrations associated with Canadian provinces, and so in this context out-of-jurisdiction and out-of-state can be used interchangeably. Not all of these registrations are necessarily cases of jurisdiction shopping – Ohio carriers may have terminals in multiple states. It is best to think of these numbers as *potential* jurisdiction shopping cases. Notice that the vast majority of these cases are clustered in a few states. The top five states – Indiana, Oklahoma, Illinois, Tennessee, and Alaska – account for 80.3 percent of the out-of-state IRP registrations associated with out-of-state plates.¹¹ While Ohio still receives money from the IRP registrations based on apportioned miles, because of the way Ohio distributes its IRP tax revenue, the counties where the vehicles are domiciled receive but a small fraction of the money.

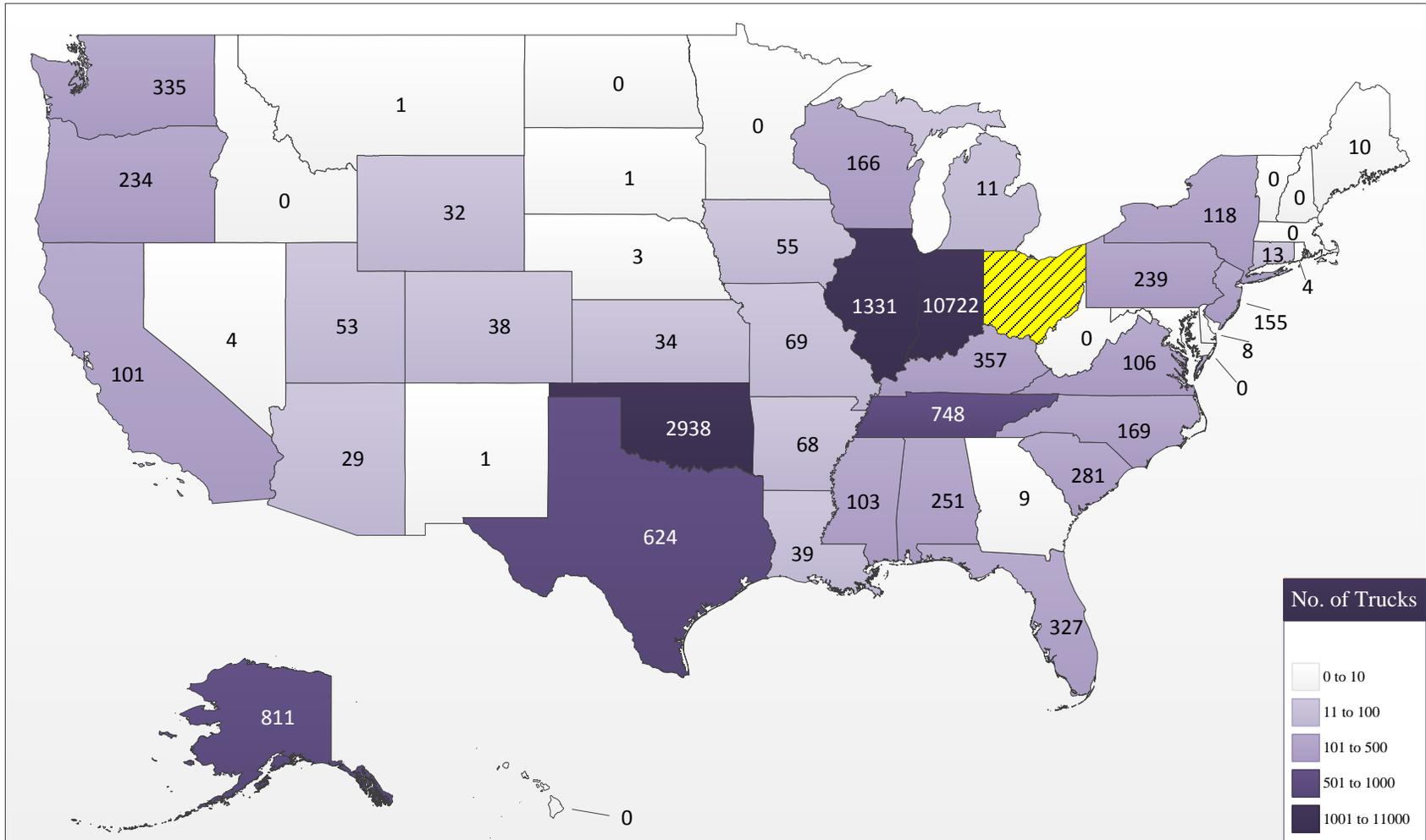
To assess county-level impacts, we first determined how many out-of-state registrations are associated with companies in county-specific taxing districts. Many of the companies are absent from the Ohio vehicle data because they do not register any vehicles in the state. Therefore, to associate a taxing district and registration (and therefore a particular county) a list of the carrier addresses maintained by FMCSA were provided to the Ohio Department of Administrative Services (DAS). (DAS) used a geolocation software application to determine the appropriate taxing district for each company, which was then matched to each vehicle by the corresponding USDOT number. Without knowing the gross registered weights of these vehicles, our best option

¹¹ Ohio does not receive money from trucks registered in Alaska because it is not a member of IRP. However, repatriating those licenses would require carriers to pay registration fees not currently going to Ohio.

was to multiply the number of vehicles times the weighted average of registration fees based on the statewide distribution of Ohio IRP registrations by weight class in 2014.¹² If we had assumed

¹² For example, 71.1 percent of Ohio IRP registrations were for 78,001 pounds and up. Therefore, the distributable amount (\$769.16) was multiplied by .711, and this was done for every weight class to derive a weighted average. Additional estimates were computed using various assumptions: a high-end estimate where every vehicle was registered with a 78,001-pound plate, a low-end estimate where every vehicle was registered with a 26,001-pound plate, and a composite of the high, low, and weighted average estimates.

Figure 7. Out-of-State IRP Registrations Associated with Ohio-Based Carriers



a specific weight class it would have biased the estimates, making them too high or too low depending on the assumption. Vehicles were also classified based on whether the registration was located in a township or a municipality because the amount of distributable revenue a county retains varies significantly according to the type of taxing district.¹³

Figure 8 illustrates the potential number of out-of-state vehicles registered to Ohio carriers by county. It shows the geographic distribution of all 20,601 out-of-state registrations based on where they registered in the county of the carrier's physical address.¹⁴ There is no way to know for certain whether these vehicles are domiciled in Ohio, but given that the registrations all belong to Ohio-based carriers, it is likely that a sizable percentage of these vehicles probably operate in Ohio. The way IRP is structured, these carriers are still remitting payments via their chosen base jurisdiction, but revenues are distributed much differently than they would be if the registration were tied to a particular county. The county where the carrier is based still enjoys some revenue, but in most cases only a fraction of what they would get if the vehicles were registered there.

The number of out-of-state registrations associated with Ohio carriers vary substantially across counties. There are 14 counties with no out-of-state registrations; additionally 50 more counties have 50 or fewer vehicles that fall into this category. There are 12 counties where there are 51 to 200 vehicles, 7 counties with 201 to 500 vehicles, and 5 counties with 501 to 6,000 vehicles. 97.3 percent of these registrations are concentrated in 24 counties, each of which has 51 or more vehicles, but the largest category in particular, with 77.3 percent in five counties. Just two counties – Clinton County (5,810) and Franklin County (4,597) – account for over 50 percent of

¹³ As noted in Chapter 1, the county gets to keep the 34 percent share if the registration is in a township, but not if the registration is in a municipality.

¹⁴ It should be noted that Alaska registrations are included in spite of Alaska's not being a member of IRP. In practice, revenue from these registrations does not go to Ohio. Apportioned registration is possible, but carriers operating these vehicles may have little incentive to register with IRP.

these vehicles. Hamilton (2,608), Cuyahoga (1,776), and Summit (1,133) Counties have the next-highest concentrations of these registrations.

Figure 8. Carrier Vehicles Registered in Other Jurisdictions, by County

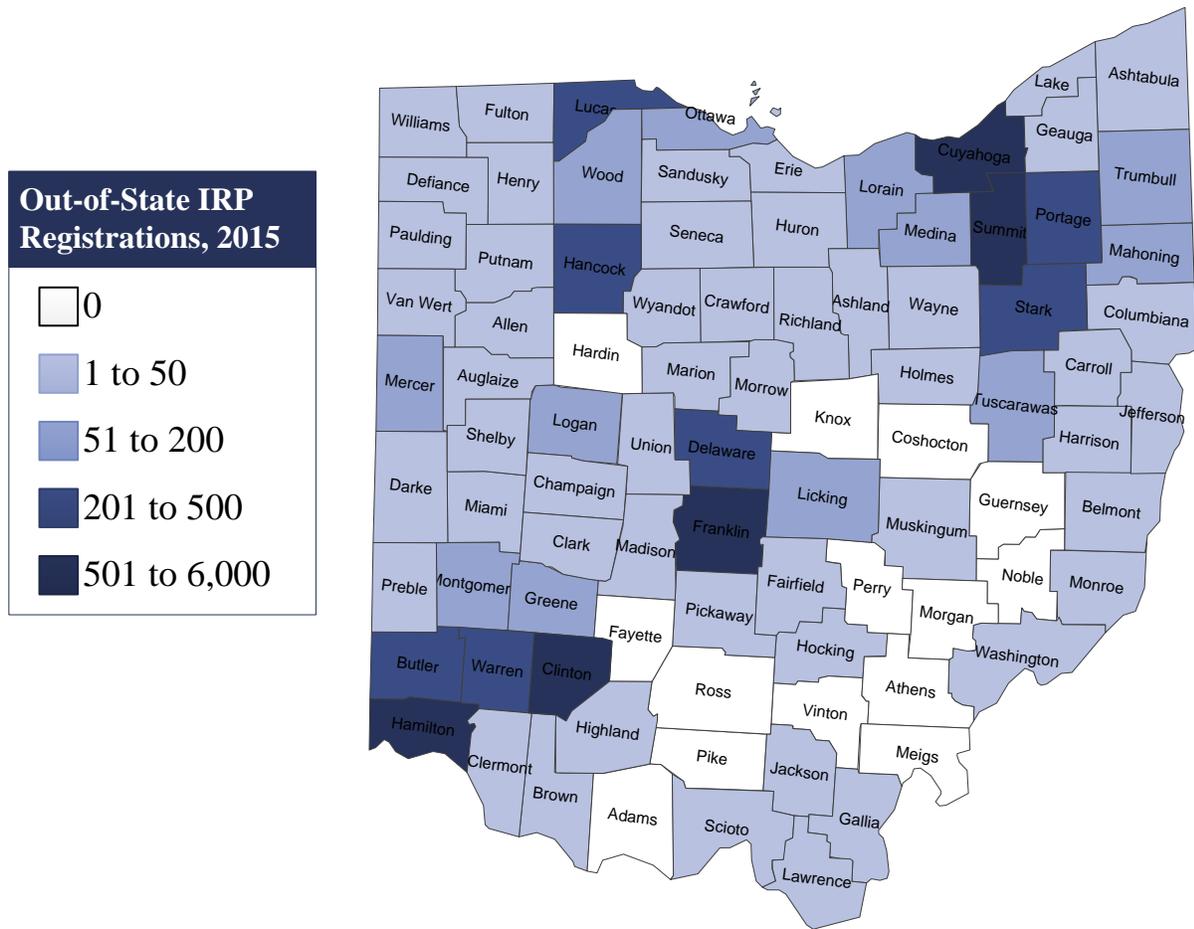


Table 8 shows the distribution of the out-of-state IRP registrations by fleet size. The first column contains fleets with fewer than 20 vehicles and the second fleets with more than 20 vehicles. Intuition suggests that the likelihood of these smaller companies' vehicles operating in Ohio is quite good, as smaller companies should be less likely to own and operate terminals in other states or jurisdictions. The numbers bear out this story, with companies in this group accounting for 88.6 percent of Ohio carriers with out-of-state IRP registrations. However, the 87

large carriers with 20 or more out-of-state registrations account for 88.3 percent of all vehicles with these registrations. Some of these vehicles probably operate outside Ohio, but if even a modest fraction of those vehicles operate within the state, larger companies exert a more pronounced effect on IRP revenue distribution because of jurisdiction shopping than do smaller carriers.

Table 8. Ohio and Out-of-State Registration Distribution by Fleet Size

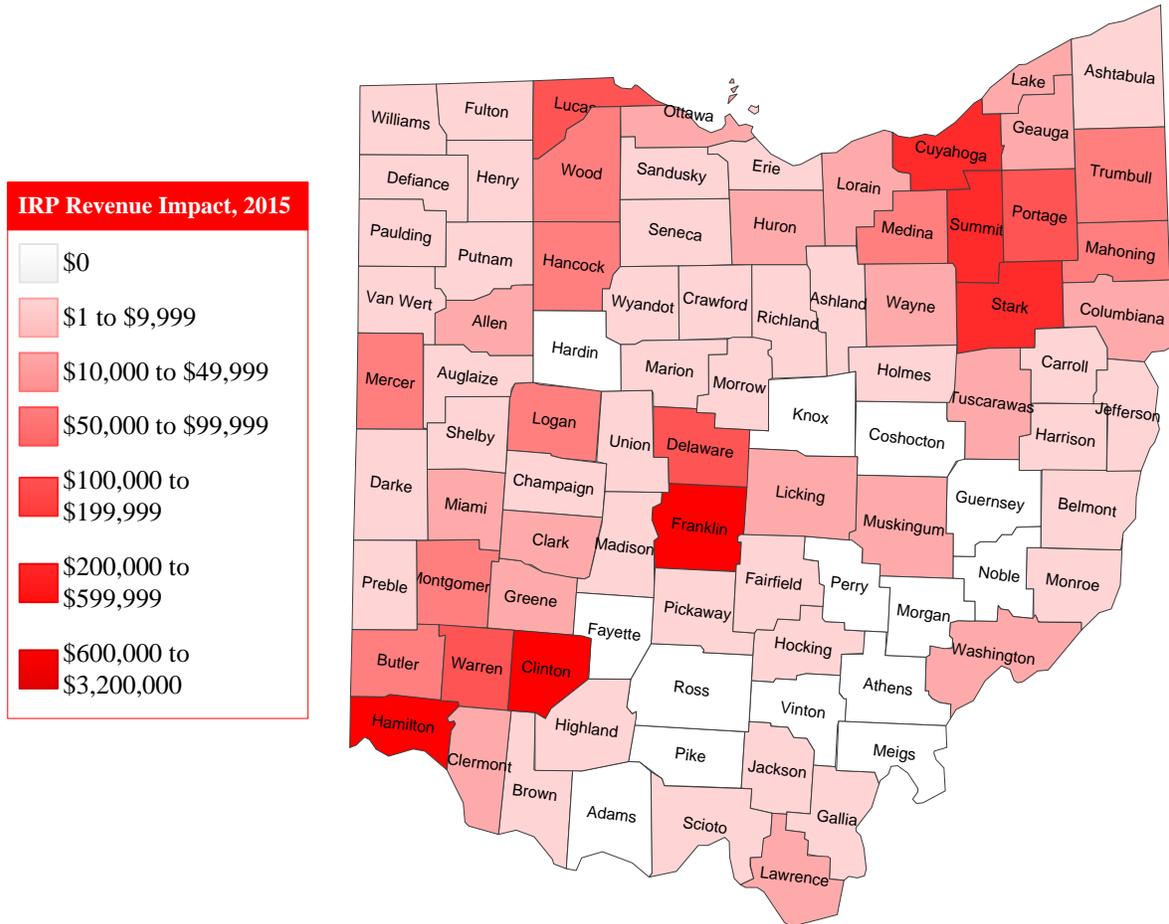
OOS Fleet Reg.	1 to 19	20 or more	Total
Total Carriers	682 (88.6%)	87 (11.4%)	769
Total Vehicles	2,412 (11.7%)	18,189 (88.3%)	20,601

Figure 9 provides the estimated direct revenue impacts on Ohio counties due to out-of-state registrations by Ohio carriers. To be clear, these estimates are only the amount of distributable revenue lost if one assumes every vehicle registered in another state should be registered in Ohio because it is domiciled in the county where the carrier’s terminal is located. Potentially, this revenue is distributed, albeit through the loss compensation and excess annual compensation mechanism, which allocates money based on all motor vehicle tax revenues (not just IRP truck revenues). It is unclear how much of this revenue would be recovered if jurisdiction shopping were curbed or prohibited because we do not know the actual number of these trucks operating in Ohio.

Furthermore, the net effect of this effect is difficult to calculate without making several assumptions and complicated calculations based on the allocation mechanisms discussed in Chapter 2. It is beyond the scope of this study. However, the purpose of this estimate is to demonstrate the degree to which various counties are impacted by IRP jurisdiction shopping – not to master the minutia of policy tradeoffs that would have to occur in wake of a resolution to this problem. It is estimated the average out-of-state truck would repatriate \$665.0138 in revenue

distributable per truck, which comes to \$13,699,949.29. These totals include distributions to counties, townships, and municipalities, but do not include administrative costs or interest accrued.

Figure 9. Estimated Direct Impact of Out-of-State Registrations on IRP Distributions



The impact ranges from negligible to significant. The total direct county impact on IRP revenue distributions is estimated at \$8.23 million for 2015. More specifically, 14 counties will see no impact; 38 counties see an impact of less than \$10,000. 17 counties experience revenue displacement between \$10,000 and \$49,999. Nine counties will lose between \$50,000 and \$99,999. Four counties will lose \$100,000 to \$199,999 in registration fees; and an additional three are predicted to lose between \$200,000 and \$600,000. The three biggest losers are Clinton County

(\$3.13 million), Franklin County (\$1.45 million), and Hamilton County (\$822,916). The reason for Clinton County’s disproportionately high losses is that virtually all of its Ohio-based out-of-state registrations are based in a township, whereas a large number of Franklin, Hamilton, and even Cuyahoga County registrations are in their respective municipalities.

Table 9 breaks down the various impacts of jurisdiction shopping by direct and indirect effect, and by district type. The direct impacts on counties, municipalities, and townships is pretty straightforward, but there are also indirect county and township impacts. These indirect impacts are based on the assumption that all 20,601 IRP registrations can and should be repatriated to Ohio as valid registrations. The small shares of all IRP registrations that go to each county and township based on mileage, as well as the equal share that goes to each county, can also be taken into account. The direct effect to counties constitutes \$8.23 million, followed by \$2.89 million to municipalities and \$6,633 to townships. The indirect effects to the county consist of the 9 percent share-based county miles and the 5 percent share that is allocated equally to each county; these effects collectively sum to almost \$1.9 million. Indirect township effects are much larger (\$678,364) than the direct effects because of the mileage-based structure of township revenue

Table 9. IRP Revenue Impacts Related to Out-of-State Registrations to Ohio Carriers

Category	Amount
Direct County	\$8,230,544.19
Direct Municipalities	\$2,886,452.50
Direct Township	\$6,633.12
Total Direct	\$11,123,629.81
Indirect County Miles	\$1,220,741.74
Indirect Township Miles	\$678,364.34
Indirect County Equal	\$677,213.40
Total Indirect	\$2,576,319.48
Total Impact	\$13,699,949.29

allocations. In total, the cumulative direct and indirect effects for counties amount to \$10.13 million, \$2.89 million for municipalities (as they have no indirect effects), and \$684,997 for townships. The total impact is just under \$13.7 million.

3.2 Revenue Trends

Another way to examine the impact of jurisdiction shopping on IRP registrations is to look at IRP revenue trends in each of Ohio's 88 counties. The revenues for each county were calculated based on what each county keeps, excluding disbursements to townships and municipalities.¹⁵ As with registration numbers, other factors can drive changes in IRP revenue, including increased or decreased economic activity in the trucking sector, differences in fees or interest, fluctuations in the ratio of municipal and township registrations, and trucking companies physically moving or terminating operations. If jurisdiction-shopping estimates are correlated with revenue changes in these areas, then jurisdiction shopping may be a primary factor in explaining why those revenue changes occurred.

Forecasting models are commonly used in the social sciences. As such, it is useful to review the context and guidance from the literature that supports the forecasts in this study. Zarnowitz identifies attributes common to successful forecasts (1992). These include verifiability of the forecast, absence of bias, use of the same variables across forecasts, and the adoption of objective methods. Incorporating all available information into the forecast is cited as another element that can be used to evaluate forecasts (Feenberg et al., 1988) and improve their accuracy (Moca & Azad, 1995).

¹⁵ Actual county-by-county revenues for 2009-2014 are provided in Appendix A. Statewide Forecasts are provided in Appendix B. Forecasts for 2015 to 2019 are provided in Appendix E.

Techniques commonly used for forecasting are trends, time series models, causal models, and accounting-type approaches (Frank, 1993). Most state governments use forecasts for revenues that rely on econometric models of varying complexity (Grizzle & Klay, 1994). These models use regressions and related economic variables to estimate future revenue collections. However, in some cases, econometric models have been shown to produce results that are functionally equivalent to those derived from simpler methods such as data extrapolation and judgment (Ahlers & Lakonishok, 1983; Armstrong, 1978; Ascher, 1981). For short-term forecasting, extrapolation has proven as successful as the complex time-series features of econometric models (Armstrong, 1984; Brandon, Jarrett, & Khumawala, 1983; Mahmoud, 1984). Irrespective of the approach taken, obtaining lengthy historical data when generating a forecast is recommended in order to improve results (Cirincione, Gurrieri, & Van de Sande, 1999; Schroeder, 1982; Downs & Rocke, 1983). Combining forecasts that use different methods can produce more accurate estimates than a single model can (Grizzle & Klay, 1994).

A number of studies have found that state revenue forecasts have been consistently underestimated (Feenberg et al., 1988; Frank & Gianakis, 1990; Klay, 1983; Albritton & Dran, 1987). Some researchers argue that forecasts in general are intentionally low in order to reduce the likelihood that reduced spending will be necessary if actual receipts fall short of the forecast (Klay, 1983; Rodgers & Joyce, 1996). Lower estimates result in small forecast errors during recessions, while errors are magnified during periods of economic growth. As forecasts are an estimate and subject to error and uncertainty, forecasters often build a buffer into forecasts to guard against unexpected declines in revenue (Rubin, 1987). Using judgment is prone to greater error than relying on data, such as cross-section or time series (Moca & Azad, 1995).

It is with these factors in mind that we turn to methods. Forecasts for future county IRP distributions from 2015 to 2019 were generated for aggregate county level distributions rather than for each part of the distribution formula across each county. To produce estimates for each part of the distribution formula, we first averaged those categories from 2009 to 2014 to obtain an average percentage. We then applied that to the forecasted total to develop estimates for the underlying parts of the distribution formula. While it is possible to apply forecasting models to these individual categories, limited historical data and the use of so many forecasting models would introduce unnecessary forecasting error to our estimates. The county level forecasts for IRP distributions were estimated using historical data from 2009 to 2014. A wider span of historical data would have likely improved the results; however, there were enough data to generate forecasts that explained over 90 percent of the variance. Attempting to predict changes in IRP distributions and the factors driving these changes beyond the five-year point would entail significant speculation and would be of limited value.

The three approaches used to generate the forecasts were a time-trend, time-trend-squared, and lag model. A time-trend model regresses historical distributions against a time variable. A time-trend-squared model follows this approach but it also squares the time variable. A lag model regresses historical distributions against the same distributions; however, the distributions are lagged by one year. The time-trend model is shown in equation (1) below.

$$Y_t = \beta_0 + \beta_1 T_t + \varepsilon_t \quad (1)$$

Y_t represents the distribution in year t , while T is the time-trend value for each year t , β_0 is the constant, and ε_t is the error term. β_1 is the value of the independent variable. The trend forecast implicitly captures various factors that are difficult to predict, such as economic changes. Nevertheless, the trend forecast error will be larger if there are sudden shifts or accelerated changes in factors that affect IRP distributions. The trend-squared variable captures exponential growth or diminishing growth rates. Equation (2) displays the time-trend-squared model, which is similar to the time-trend model.

$$Y_t = \beta_0 + \beta_1 T_t + \beta_2 T_t^2 + \varepsilon_t \quad (2)$$

The lag model, more formally known as the autoregressive (1) model¹⁶, exploits the relationship between the current year's distribution and the previous year's distribution to future distributions. It relies heavily on prior-year distributions to forecast successive years. Equation (3) below shows the lag model. Y_{t-1} is the prior year's revenue. The coefficient on the lag model is essentially the percentage of last year's revenues that are added to the constant to obtain the predicted value.

$$Y_t = \beta_0 + \beta_2 Y_{t-1} + \varepsilon_t \quad (3)$$

¹⁶ Autoregressive (1), or AR(1) model relies on the previous term in the process to predict the next term. In this case, that means that prior year revenue is used to predict current year revenue and so on.

In order to generate the forecasts, we then averaged the resulting estimates from each of the models. Still, each model was checked for goodness of fit and significance, with attention paid to the resulting estimates (compared to the historical data). In some cases, a downward trend in the historical data yielded values in outlying years that indicated negative distributions. These were unrealistic, thus when this occurred the forecast method was removed from the average calculation entirely. The regression results for each model are shown in Appendix I.¹⁷

Table 10. Statewide IRP Distribution, County Share, 2009-2019

Year	County IRP Share
2009	\$30,357,776
2010	\$31,433,750
2011	\$33,257,341
2012	\$34,133,826
2013	\$34,102,690
2014	\$36,380,037
2015*	\$37,826,661
2016*	\$39,612,134
2017*	\$42,413,268
2018*	\$48,150,890
2019*	\$62,085,832

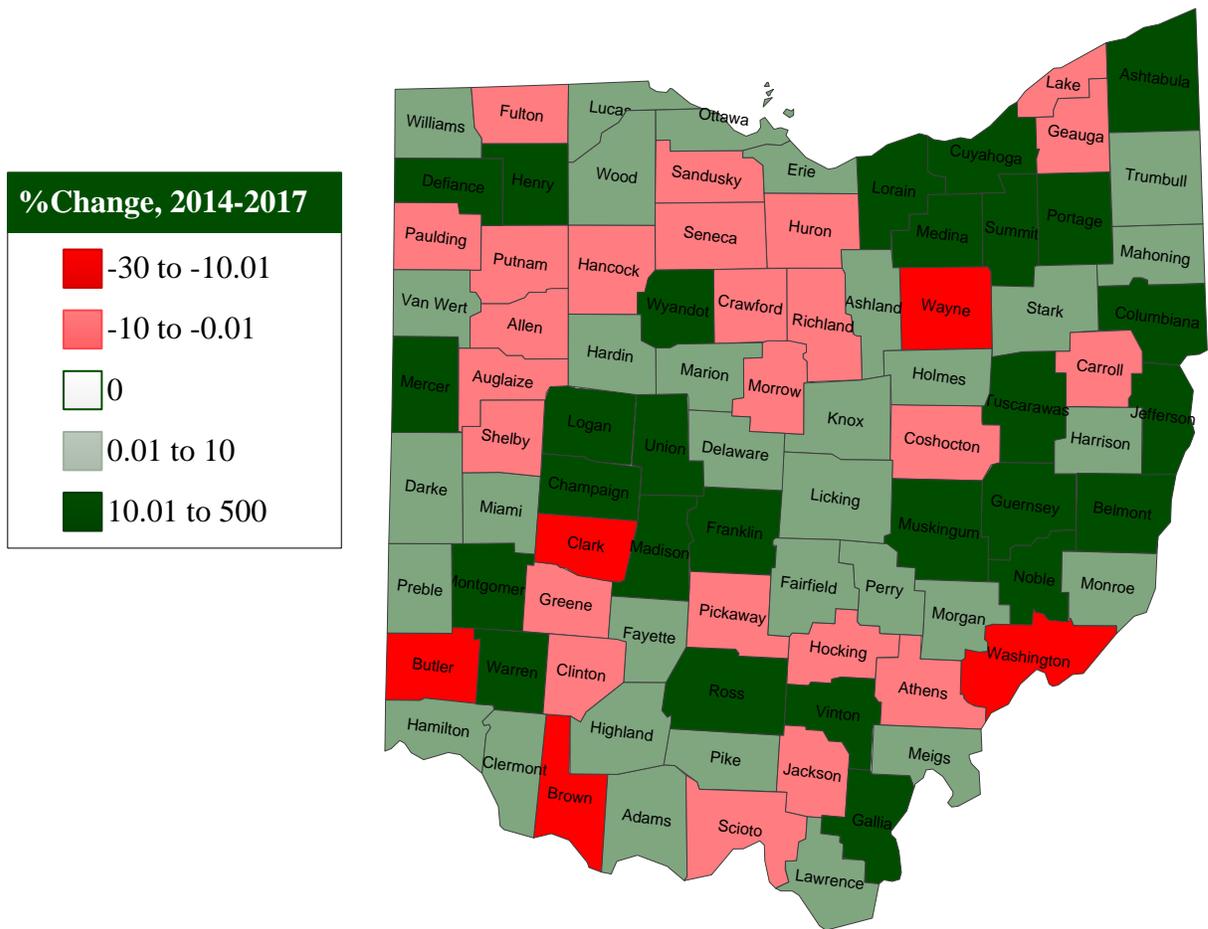
*Projected

To put these projections in context and simplify the interpretation of our results, the future statewide projections are shown in Table 10. The totals are based on the sums of county-level forecasts. Included are actual numbers from 2009 through 2014. The revenue projection is the amount the counties are expected to keep; it does not include final distributions to municipalities or townships. The projections increase slowly at first. Increases accelerate significantly in 2018 and 2019. The time-trend-squared models are primarily responsible for this sharp uptick, which

¹⁷ County Time-Trend Forecasts are the time-trend model, County Time-Trend-Squared Forecasts are the time trend-squared model, and County Lag Forecasts are the lag model. For the County Time-Trend Forecasts, year is the time variable, year² is the squared term in County Time-Trend-Squared Forecasts, and the lagged value for the County Lag Forecasts is var2 for Adams County, var4 for Allen County, and so on.

should be interpreted cautiously, as the other models do not show as strong of an increase. Beyond the three-year mark, the time-trend-squared model diverges substantially from the time-trend and lag models. Our future economic prospects are uncertain, however. For example, if a deep recession were to occur during the forecast period, even the more conservative forecast models may overestimate revenues.

Figure 10. Forecasted Change in County IRP Revenue, 2014-2017



Despite uniform upward trajectory in IRP county revenue forecasts at the state level, the individual county projections look quite different. The variation is based on the individual trend line for each county, which typically has greater volatility (and therefore statistical noise) than the state-level forecast. The forecasted percent change in revenue between 2014 and 2017 is reported in Figure

10. Positive revenue trends are indicated in green, and negative revenue trends in red. Lighter shades of either color indicate a change of 10 percent or less over the time period, whereas darker shades of red and green signify a change of more than 10 percent.

The Figure 10 forecast anticipates three-year growth over 10 percent in 27 counties, and growth of less than 10 percent for an additional 32 counties. As such, we expect revenue growth in 59 of Ohio's 88 counties. Conversely, 24 counties have a projected loss of revenue of less than 10 percent, and in five cases we expect declines larger than 10 percent. Overall, the revenue picture appears to be positive in most contexts. However, a non-negligible number of counties face declining revenues, just as local funds for highway infrastructure maintenance and enhancements from federal and state sources are stagnating. Even in counties where the forecasts project revenue growth, IRP funds are not distributed as equitably as many officials would like.

A correlation coefficient, which measures the strength of association between two variables, was calculated to relate the number of out-of-state vehicles in each county to the percent change variable used to create Figure 10. The resulting coefficient (.033) was weak, which indicates there is little association between out-of-state vehicles and projected revenue changes. The lack of association does not mean out-of-state jurisdiction shopping is disconnected from revenue losses. Given that these vehicles are typically never registered in Ohio, the impacts would not appear in a model that does not use out-of-state registrations to project revenue effects. Our intuition was that the forecasting models might be driven by indirect economic effects, but these trends are independent of the jurisdiction shopping issue. There are positive revenue projections for counties in which potentially large numbers of out-of-state registrations are domiciled (e.g. Mahoning County), and negative projections for counties where jurisdiction shopping is not a significant issue (e.g. Brown County).

Chapter 4. Case Studies

Statewide discussion of the IRP tax distribution, the registration trends and jurisdiction shopping phenomenon, revenue impacts, and revenue forecasts clarify several of the problems with IRP jurisdiction shopping that reverberate in Ohio. However, to appreciate fully the intricacies of the policy issue it behooves us to examine the particulars of this problem at the county level. Specifically, this section develops case studies to provide additional insights into factors not evident from the high-level quantitative analysis. The case studies provide greater detail about issues that emerged from surveys and from conversations with county engineers.

We sent surveys to engineers asking them about trucking industry practices in their county. Questions asked respondents to identify large fleets (50+ vehicles), whether they have noticed a substantial number of commercial vehicles garaged in the county with out-of-state plates, if they have received requests for road improvements by local businesses, the degree to which road improvements are necessitated by heavy volumes of truck traffic, the significance of jurisdiction shopping in their county, the state of IRP revenue disbursements, the degree to which revenue changes may be associated with jurisdiction shopping, and whether they would support changes to the mechanisms that distribute IRP registration fees for large fleets registered out-of-state but domiciled in Ohio. Nineteen of the 88 counties returned surveys, including:

- Allen
- Carroll
- Champaign
- Columbiana
- Coshocton
- Darke
- Defiance
- Geauga
- Greene
- Lake
- Lawrence

- Logan
- Madison
- Mahoning
- Mercer
- Morgan
- Richland
- Sandusky
- Shelby

The responses provide additional information to consider when developing potential policy solutions for the IRP revenue distribution problems.¹⁸ In some cases, county engineers cited examples of companies missed in the impact study. Several companies moved their registrations out-of-state before 2009, when the available vehicle data starts. Additionally, distribution centers for large multi-state companies were left out of the impact analysis. These companies have primary addresses in other states, so their out-of-state IRP registrations did not emerge during the matching process. Nevertheless, several hundred trucks are domiciled in these distribution centers, which are located throughout Ohio. Verifying these registration numbers is difficult, as carriers have been reluctant to respond to county engineers' requests for information about the size of their fleets. In several cases engineers reported large companies do in fact maintain local registrations. Each case is different.

A few county engineers reported having been approached by representatives of out-of-state trucking companies or by economic development officials in Ohio about upgrading access roads, intersections, and other highway infrastructure near their distribution centers. The difficulty is that engineers have few resources to make such upgrades because only a very small fraction of the registration fees actually make it back to their counties when vehicles are registered in other jurisdictions. Ohio County Engineers would like to assist with economic development and local

¹⁸ Other county engineers provided additional information but did not fill out the survey.

industry needs, but they lack funding to make some of the requested improvements in areas that have lost funding due to jurisdiction shopping.

Specifically, shale-drilling companies have approached at least one Ohio County Engineer about improving roadways that were originally designed to handle agricultural and residential traffic. They sought enhancements that would make the roads amenable to vehicles and traffic levels associated with the industry. Large distribution companies have proposed projects related to terminal or distribution center expansions. Further, heavy truck traffic requires substantial road maintenance that has not been requested but is nevertheless necessitated by motor carrier operations. These projects may include resurfacing, in-place recycling, full-depth repairs, mill and fill, installation of traffic signals and turn lanes, as well as additional projects specific to particular requests. Some engineers reported they have not received these requests.

When asked whether they would support changes to IRP registration distribution methods to help counties with large fleets offset losses due to jurisdiction shopping, most engineers agreed. Specifically, 12 of 19 engineers responded “yes” or provisionally agreed, assuming that the resulting impact did not cost their county revenue or impact Roadway Use and Maintenance Agreement (RUMA) processes currently in place. Five others were unsure how severely the problem affected their county, or they requested more information about the issue. Those engineers who did not support changes usually cited concerns about revenue losses. One engineer contended that most large companies have distribution centers by interstates and do not make heavy use of local roads.

Some engineers noted that alternative approaches – aside from changing the revenue distribution – might be warranted. One respondent suggested tax credits might help counties attract economic development and persuade businesses to site facilities locally. Another respondent

suggested looking at the administrative costs that Ohio's Departments of Transportation or Public Safety recoups from IRP revenues, and determine whether those administrative costs could be reduced or shared more equitably. Another engineer suggested a cost-sharing mechanism be put in place for companies that operate vehicles in multiple counties so that registration fees are shared based on actual operations.

Based on our survey results and the empirical evidence analyzed in Chapter 3, four counties will be profiled in this chapter: Clinton County, Mahoning County, Franklin County, and Butler County. We selected Clinton County because it is where jurisdiction is most consequential; it has cost the county millions in IRP revenues. We chose Mahoning County because it has several significant issues not obvious from our quantitative analysis. The quantitative analysis missed some of problems that have arisen due to jurisdiction shopping. Franklin County was included because we estimated its losses were second highest behind Clinton County. However, Franklin's issues are somewhat different because most of the jurisdiction shopping has been pursued by carriers located in a municipality rather than a township. Butler County was chosen because it also faces a number of unique challenges, including a decline in registrations from 2012 to 2013, a large out-of-state impact due to jurisdiction shopping, and a shared border with Indiana, the state where the vast majority of out-of-state registrations are logged.

Case Study 1: Clinton County

Clinton County is located in southwestern Ohio. According to the U.S. Census Bureau's 2014 estimate, it has a population of 41,835. The Bureau's County Business Patterns data indicates there were 888 workers employed by 13 establishments in the truck transportation industry in 2012.¹⁹

¹⁹ According to the U.S. Census Bureau's North American Industry Classification System, the truck transportation industry is a subsector of the transportation and warehousing industry. It related to transportation of cargo using motor vehicles, namely tractor-trailers and other trucks.

The annual payroll in 2012 for this industry was approximately \$33.4 million. According to the Ohio's IRP vehicle data, there were 258 vehicles registered to 71 distinct USDOT numbers in Clinton County during 2013²⁰ ²¹. For 2015, The number of out-of-state vehicles registered to Ohio carriers in the initial impact analysis of Clinton County was 5,810 – the largest of any county. Based on that vehicle count, the estimated IRP impact on the county (excluding townships and municipalities) is \$3.13 million for the current year.

Clinton County's situation revolved almost entirely around a single carrier based in Wilmington. In 2008, the Ohio-based carrier decided to move all of its IRP truck registrations from Clinton County to Indiana. Current vehicle registration records indicate the company has 5,804 trucks registered in Indiana, which are all but six of the out-of-state vehicles registered in the county. Attempts by Clinton County Engineer Jeff Linkous to convince the company to repatriate those registrations to Ohio have so far been unsuccessful.

According to the *Wilmington News-Journal*, the company moved its IRP licensing because it was easier for the company to register online, and there were significant cost savings associated with registering the plates in Indiana (Huffenberger, 2015). Cost reductions stemmed from a reduction in the company's administrative effort to register trucks in Indiana as compared to the effort required to register the trucks in Ohio. Fees unrelated to the specific IRP registration costs also contributed to cost reduction. These additional fees, Linkous estimated, amounted to \$75,000 for the company for 5,000 vehicles. This is a fraction of the windfall the county would enjoy were the registrations reverted to Ohio. The company still must remit IRP registration fees to Ohio, but

²⁰ The Census Bureau defines an establishment as a physical location where business is conducted and industrial operations are held. The discrepancy between establishment numbers and USDOT numbers is difficult to reconcile, but registration records do not necessitate a physical place of business – just the use of equipment.

²¹ The Ohio BMV's official IRP truck vehicle registration tally was 245 in 2013.

only a small portion of those fees go to Clinton County because of the distribution mechanisms. Linkous noted that the funds would make more maintenance, enhancements, and repairs possible. Representatives for the company said that it would provide Ohio assistance in improving its own registration process and is still committed to the well-being of Clinton County. They mentioned plans to expand corporate headquarters, which would bring an additional 200 jobs to the area. Of course, neither of these factors improve revenue shortfalls that challenge local and state officials responsible for maintaining roads in Clinton County.

According to a 2014 estimate assembled by the Tax Distribution Section of the ODPS, Clinton County has lost an estimated \$2.6 million a year in IRP distribution revenue.²² Our estimate is even higher, at \$3.13 million. The difference is based on the assumptions made in the methodology of both estimates. The earlier ODPS estimate is based on former registrations held in 2008 (4,775), and includes the specific plates associated with each vehicle. Their estimate also included other fees and taxes beyond the scope of this study. Nevertheless, when our methodology is used on the same number of vehicles, the estimated impact is \$2.58 million, which is very close to the ODPS estimate. Because specific weight information was not available, we assumed a distribution similar to the state's overall IRP distribution. In addition, administrative fees and interest were not taken into account in our estimate.

Figure 11 shows the projected IRP revenues for Clinton County from 2015 through 2019. Instead of using the weighted average of the three forecasts (which is used in the IRP calculator tool created as part of this analysis), only the time trend is shown here.²³ Time trends tend to be somewhat conservative and more likely to yield positive revenue trends over the long term

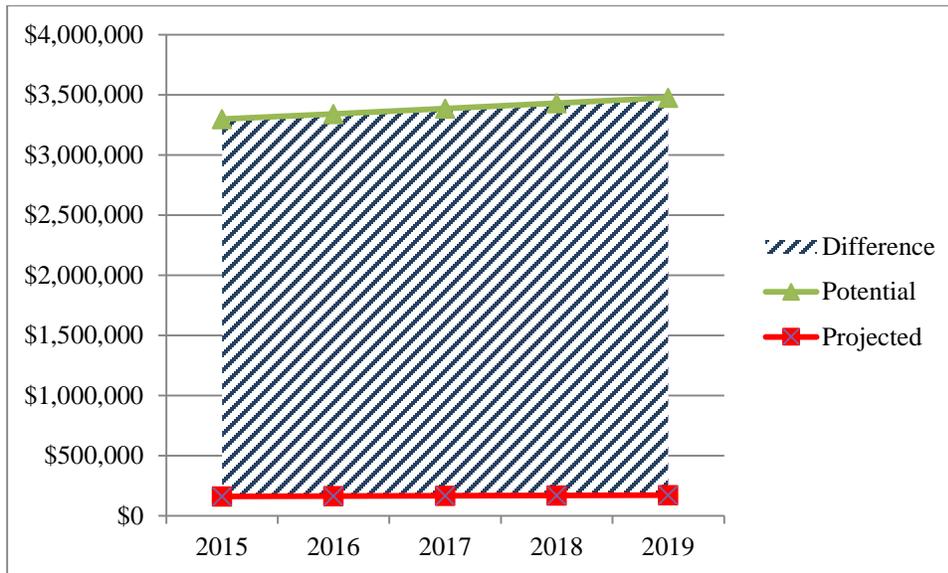
²² The ODPS estimation is included in Appendix G.

²³ We used the time-trend models here because their predictions for revenue trends tend to be more modest, which is consistent with our knowledge about the historical trends of registration revenue in several states.

compared with the other models, but their year-to-year changes are less pronounced. The trend-squared model and lag models show stagnating or even declining IRP revenues for Clinton County.

Regardless of which forecast proves correct, the impact will only

Figure 11. Clinton County IRP Impact Forecast, 2015-2019



be a fraction of the potential revenue the county would collect if the county’s outstanding registrations we repatriated to Ohio. The impacts were calculated for 2015 based on the methodology described in section 3.1 and indexed according to its 2015 proportion of the time-trend forecast for 2016-2019. The model shows the projected revenue with the red square plot. Potential revenue that could be collected if all of the county’s out-of-state registrations were returned to Ohio is depicted by the green triangle plot. The shaded area between the two represents the difference – or impact – to the county.

Projected revenue, under the current registration arrangement, increases from \$163,456 in 2015 to \$172,232 in 2019. If the slow, steady growth of the time-trend forecast persists, the total revenue for Clinton County over the five-year forecast period is \$839,220. If the out-of-state registrations (which are the current out-of-state registrations corresponding to companies located

in the county) were repatriated, the potential revenue recouped over this period would be \$16.93 million. The potential difference to Clinton County over a 5-year period would exceed \$16 million. A shift of this magnitude would dramatically change the outlook for county road maintenance and enhancements in Clinton County.

Case Study 2: Mahoning County

Mahoning County is located in northeastern Ohio, and according to the U.S. Census Bureau's 2014 estimate has a population of 233,204. According to the Bureau's County Business Patterns data, there were 1,224 workers employed by 87 establishments in the truck transportation industry in 2012. The annual payroll for the industry in 2012 was approximately \$54.3 million. According to the Ohio's IRP vehicle data, there were 3,885 vehicles registered to 324 distinct USDOT numbers in Mahoning County during 2013.²⁴ The number of out-of-state vehicles registered to Ohio-based carriers in the initial impact analysis of Mahoning County was 127 for 2015. Based on that vehicle count, the estimated IRP impact on the county (excluding townships and municipalities) is \$68,133 for the current year.

The impact analysis as originally conceived does not fully account for all of the potential jurisdiction shopping issues in Mahoning County. Mahoning County Engineer Randy Partika provided examples of companies with distribution centers located in the county but whose primary addresses are listed in other jurisdictions. These carriers were not included because without firsthand knowledge there was no way of knowing which carriers with primary addresses outside Ohio have distribution centers in the state. The two examples are large distribution companies that plate in Indiana. Both house approximately 100 trucks at their distribution centers, adding 200 trucks to the original estimate. One of the two companies is expanding a terminal, which will

²⁴ The Ohio BMV's official IRP truck vehicle registration tally was 3,928 in 2013.

translate to an additional 100 trucks in the area, with the possibility of adding 100 more. Thus, Mahoning County will soon have 300 to 400 trucks using its roadways that were not accounted for in the original impact estimate.

To recalculate the impact analysis and index it to the time trend forecast, we added 300 trucks to the current Mahoning County out-of-state IRP registration estimate of 127. This yielded an estimate of 427 out-of-state registrations for Mahoning County in 2015, although depending on the speed of the companies' expansion some of these registrations may not be a factor until next year. Each of the additional vehicles would be registered with a township instead of a municipality, which equates to 425 township registrations and 2 municipality registrations. The estimate still uses the weighted plate average, which may be a bit conservative, as most of the trucks are said to be 18-wheelers, which usually register on the 78,001-pound plate. The 2015 impact estimate grows from \$68,133 to \$230,145. It is plausible that such carriers are operating around the state under similar circumstances, and paying indirectly to the state's out-of-state funds netting transactions, which are applied to existing in-state registrations as loss compensation and to the annual excess compensation distribution.

Another factor contributing to the Mahoning County situation is that jurisdiction shopping at one time had far greater impact than it does currently. Mahoning County's registrations dropped from 3,625 in 2008 to 2,858 in 2009 and stabilized in 2010. Most of that drop was due to the loss of another large company that also moved its registrations to Indiana. According to the ODPS impact estimate, this move cost Mahoning County \$445,029 annually.²⁵ Partika had discussions with company executives about how out-of-state registrations influenced the distribution of IRP registration fees. Once aware of the issues, the company agreed to switch its registrations back to

²⁵ The ODPS estimate is provided in Appendix H.

Mahoning County in 2010, thereby stemming the losses. Had this situation persisted, our estimates indicate that Mahoning County would potentially lose nearly \$700,000 each year in IRP disbursements. However, the process of convincing a carrier to repatriate can be difficult and time-consuming task. In Partika’s opinion, carrier-by-carrier negotiations are not a viable long-term strategy.

Figure 12. Mahoning County IRP Impact Forecast, 2015-2019

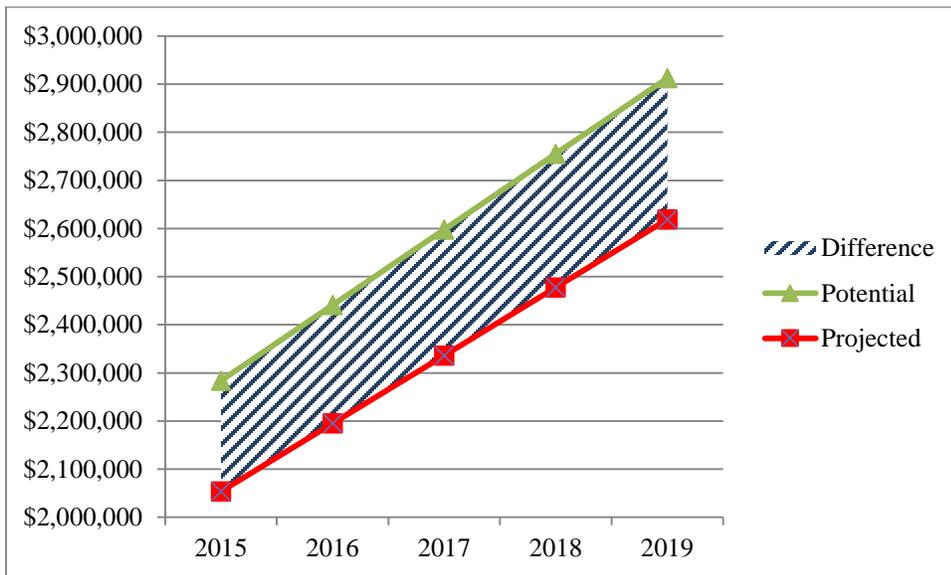


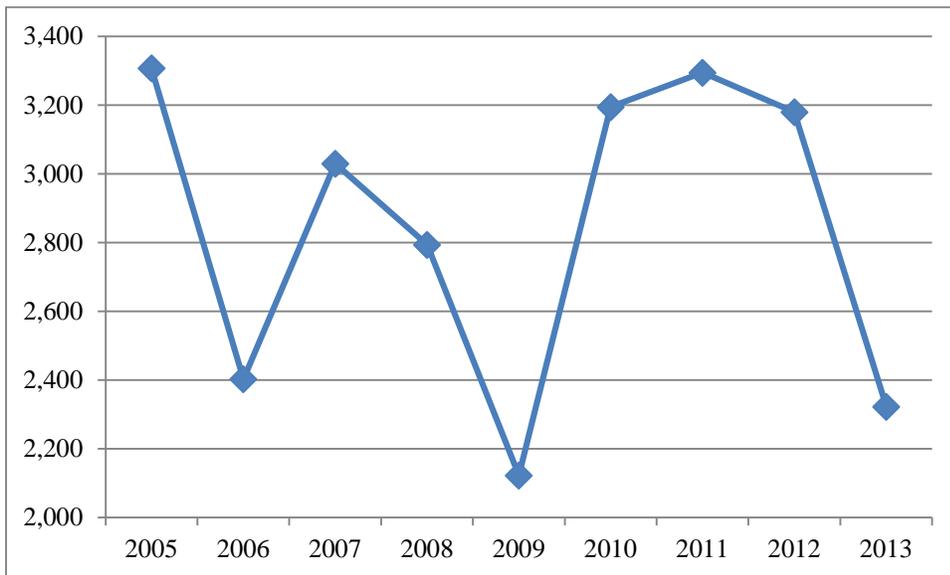
Figure 12 shows the time-trend forecast for Mahoning County for 2015 to 2019. The time-squared-trend forecast indicates that revenues will stagnate at roughly \$1.8 million for the entire period, the lag model shows a precipitous drop, and the weighted model suggests gradual drop in revenues. The time-trend model is the most optimistic of the four forecasts created for this particular county. To reiterate, time-trend forecasts created with only six years of back data tend to be volatile and noisy, and as such are subject to considerable variation. Projected revenue increases steadily from \$2.05 million to \$2.62 in 2019, which means the total IRP revenue for Mahoning County totals \$11.68 million over the five-year period. If all out-of-state registrations

with Ohio carriers in located Mahoning County were reestablished in the state, the additional registrations would contribute \$1.31 million in additional revenue between 2015 and 2019.

Case Study 3: Butler County

Butler County is located in southwestern Ohio, and according to the U.S. Census Bureau's 2014 estimate has a population of 374,158. According to the Bureau's County Business Patterns data, there were 3,412 workers employed by 115 establishments in the truck transportation industry in 2012. The annual payroll for the industry in 2012 was approximately \$168.8 million. According to the Ohio's IRP vehicle data, there were 2,585 vehicles registered to 344 distinct USDOT numbers in Butler County during 2013.²⁶ The number of out-of-state vehicles registered to Ohio-based carriers in the initial impact analysis of Butler County was 204 for 2015. Based on that vehicle count, the estimated IRP impact on the county (excluding townships and municipalities) was \$97,641. Butler County's registration history is quite unusual.

Figure 13. Butler County IRP Registrations, 2005-2013



²⁶ The Ohio BMV's official IRP truck vehicle registration tally was 2,323 in 2013.

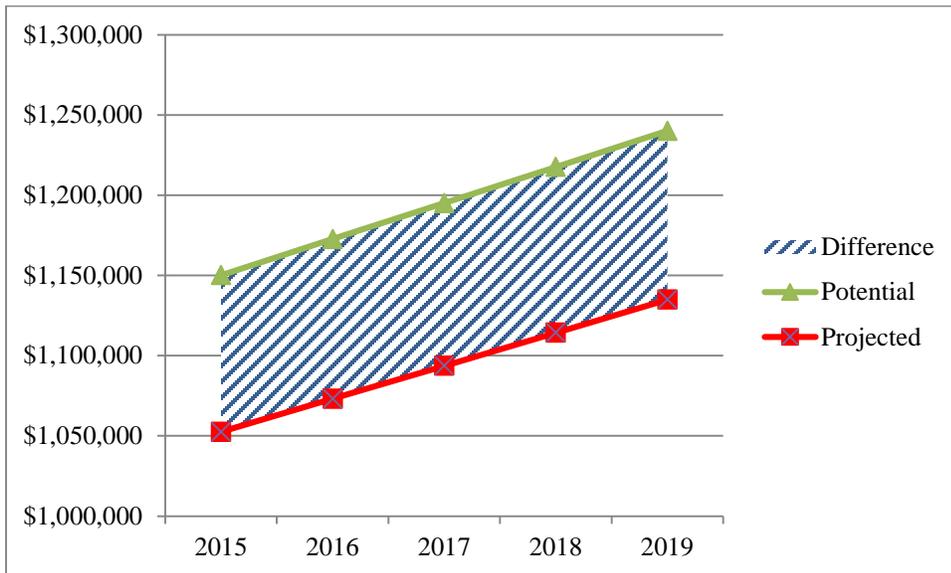
Figure 13 indicates that Butler's registration totals dropped abruptly between 2012 and 2013 from 3,180 to 2,323. In fact, the registration patterns have been somewhat erratic for the entire period for which county-level figures are available. Registrations dropped from 3,308 in 2005 to 2,403 in 2006, before returning to 3,030 in 2007. They dipped slightly in 2008 before plummeting in 2009, sharply rising in 2010, and stabilizing for two years before plummeting again in 2013. The IRP impact analysis found 204 vehicles plated in other states that belonged to carriers located in Butler County. The large variability in these data suggests there were erratic business and economic patterns or even cases of jurisdiction shopping not picked up by the initial analysis.

The forecast and potential impact for 2015 through 2019 is depicted in Figure 14. The projected increase in revenue runs from \$1.05 million in 2015 to \$1.13 in 2019. This is a very slight increase, and might be on the high side if the alternative forecasts are better predictors of future revenues. The time-trend-squared model predicts stagnant revenues, and the lagged and averaged models predict a substantial decline in revenue. However, sticking with the time-trend model, the expected impact rises from \$97,641 in 2015 to \$105,281 in 2019. Over the five-year period, projected revenue is \$5.47 million, but this number would increase to \$5.98 million if the out-of-state registrations of vehicles housed in the county were registered in Butler County. This would push up the estimated impact over the same period to \$507,304. These IRP impacts are not as large as in Clinton, Mahoning, or Franklin Counties, but the distortion may have a negative impact on the county engineer's ability to maintain local roads.

In 2013, *The Journal-News* reported that Butler County officials approved a local tax abatement to assist a multistate carrier with the expansion of its operations in Hamilton (Schwartzberg, 2013). The company, which has nearly 1,300 registered IRP vehicles, has its primary address in Wisconsin. Of its fleet, there are 13 vehicles registered in Ohio, but we cannot

know if that reflects the number of vehicles domiciled in the county without more follow up. Another reason for the erratic registration numbers is that another large company had 627 registrations in Butler County in 2012, but all of those registrations disappeared in 2013. The associated USDOT number is no longer active, and it is not clear whether this business ceased operations, moved operations, or turned transit over to another freight and logistics company. Both of these companies may impact on the IRP registrations that do not register in the impact estimate and forecast provided in Figure 14.

Figure 14. Butler County IRP Impact Forecast, 2015-2019



Case Study 4: Franklin County

Franklin County is located in central Ohio, and according to the U.S. Census Bureau’s 2014 estimate has a population of 1,231,393. Based on the Bureau’s County Business Patterns data, there were 8,845 workers employed by 340 establishments in the truck transportation industry in 2012. The annual payroll in 2012 was approximately \$370.8 million for those employees. According to the Ohio’s IRP vehicle data, there were 9,560 vehicles registered to 783 distinct

USDOT numbers in Franklin County during 2013.²⁷ The number of out-of-state vehicles registered to Ohio-based carriers in the initial impact analysis of Franklin County was 4,597 for 2015. Based on that vehicle count, the estimated IRP impact on the county (excluding townships and municipalities) was \$1.45 million for the current year.

Franklin County has more out-of-state vehicles registered to its carriers than any other county except Clinton County. Unlike Clinton County, there are 88 Franklin County carriers of various sizes that have out-of-state IRP registrations. The county has 9 carriers with 50 or more trucks registered in another state, and 8 more with 10 to 21 carriers registered in another state. These 17 medium- and large-sized carriers account for 96.5 percent of all out-of-state registrations in Franklin County. Nevertheless, having the out-of-state registrations spread across 17 distinct carriers poses a greater challenge for the County Engineer's Office than if a single carrier were responsible.

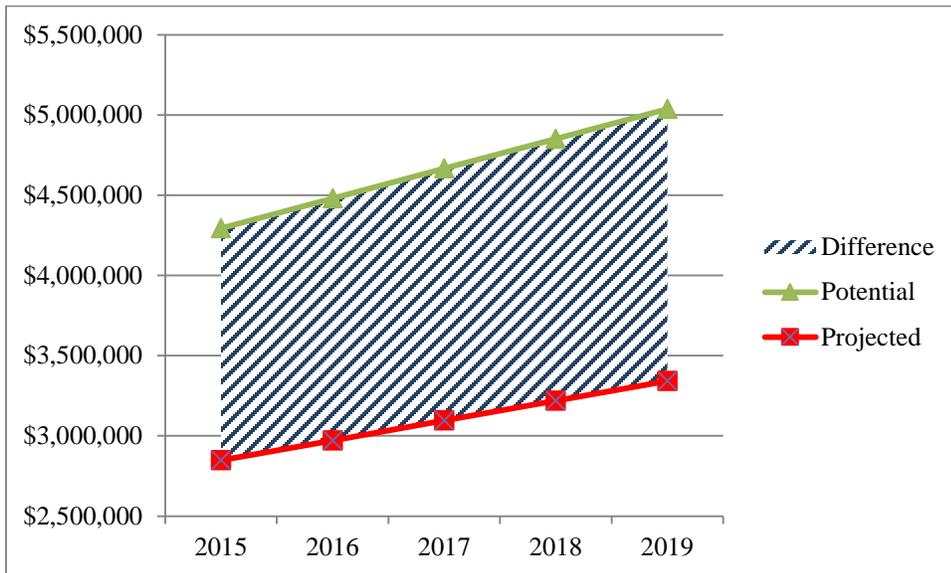
A complicating factor is the distribution of carriers among municipal taxing districts. Franklin County is essentially the inverse of Clinton County in that 99 percent of all its out-of-state registrations are in municipal taxing districts. This means a smaller potential revenue impact to the county because a large chunk of those revenues will go to the municipalities in the county. This study has focused on the impact to the counties, but other Ohio taxing districts are affected by jurisdiction shopping, particularly municipalities. The 2015 revenue impact for Franklin County municipalities is \$1.03 million. The overall township impact is only \$1,335 – an amount that gets divided between each of the townships in Franklin County.

Figure 15 reports the Ohio IRP revenue projections for Franklin County from 2015 through 2019 as well as the potential revenue the county would collect if its carriers with out-of-state

²⁷ The Ohio BMV's official IRP truck vehicle registration tally was 9,715 in 2013.

registrations repatriated them to Ohio. The projected revenue based on the time-trend forecast increases steadily from \$2.85 million in 2015 to \$3.3 million in 2019. All of the forecasting models project IRP revenue increases for Franklin County, with the time-trend model being the most conservative. As noted previously, the out-of-state revenue impact is calculated to be \$1.45 million and is projected to increase to \$1.70 million by 2019. The five-year impact for out-of-state registrations on Franklin County IRP revenues is \$7.86 million, and would be the difference between \$15.48 million projected and \$23.33 million potential revenue over that time.

Figure 15. Franklin County IRP Impact Forecast, 2015-2019



Chapter 5. Conclusion

The primary objective of this study was to determine the degree to which jurisdiction shopping impacts the distribution IRP registration fees to Ohio counties and taxing districts. Jurisdiction shopping occurs when a carrier based in one state registers vehicles in another state, usually to avoid related taxes, fees, or for greater convenience if another state has a more streamlined registration process. Some county engineers in Ohio have noticed large fleets of trucks operating in their area but registered in another state. As a result, our analysis focused on the county level because most of the IRP revenue goes to counties, and not to townships or municipalities.

Ohio's motor vehicle license taxes are distributed based on a complex distribution formula. It contains distribution allocations for state use, administrative costs, and distributable revenue and interest for counties and taxing districts. Chapter 1 outlined this mechanism in detail. Essentially there are two pools of funds: in-state IRP registrations and out-of-state IRP registrations. Because IRP registrations are prorated according to the mileage reported in each state, only a percentage of the registration fees stay in Ohio. To alleviate the negative impacts of this arrangement, Ohio supplements the distributable revenue with out-of-state registration revenue so that local taxing districts receive the same amount of revenue that they would have from an intrastate truck plate. At the end of each year, remaining revenue is apportioned through the annual excess compensation, which allocates revenue based on each county's share of all motor vehicle license tax revenue, not just license revenue from interstate commercial trucks.

Registration location is what anchors the funding to the taxing district. Carriers can legally register their vehicles in another state, but when they do, the money once intended for the county, city, or town they are located in flows into the out-of-state revenue pool. The money is used for loss compensation of the remaining in-state registrations or is distributed in the annual excess

compensation distribution, which uses different criteria for disbursement. The state receives the same amount of IRP fees from these carriers, but it is apportioned much differently compared to when those carriers register in the state. As a result, counties where this practice is most common are losing a substantial amount of revenue.

Registration trends from 2009 to 2013 provide an interesting context in which to analyze jurisdiction shopping by Ohio-based carriers. Even using vehicle data to track IRP registrations over time makes it difficult to identify vehicles that were once registered in Ohio but are now registered in another IRP state. A better approach – and the one adopted during analysis – is to identify Ohio-based carriers with vehicles plated elsewhere. This method revealed 20,601 vehicles registered to carriers whose primary address listed in Ohio. The vast majority of these trucks belong to carriers with medium-to-large fleets. We cannot know for certain how many of these vehicles are domiciled or garaged in the state. However, following the basic ideal that every truck belonging to an Ohio-based carrier is apportionable and should be registered in-state, it is possible to calculate the revenue impacts of these registrations.

In 2015, the statewide revenue effects due to jurisdiction shopping were estimated at \$10.13 million for counties, \$684,997 for townships, and \$2.89 million for municipalities. These estimates assumed the additional revenue that would accrue to each Ohio taxing district if every IRP truck belonging to an Ohio carrier bore an in-state registration. The direct, county-specific impacts (excluding townships, municipalities or indirect county impacts) vary greatly from county to county. In 14 counties, there was no impact; another 38 counties saw an impact of less than \$10,000. Seventeen counties had revenue displacement between \$10,000 and \$49,999. The next nine counties faced more substantial losses: between \$50,000 and \$99,999. The study estimated that four counties would lose between \$100,000 and \$199,999 in registration fees. Three other

counties lost between \$200,000 and \$600,000. The three biggest losers were Clinton County (\$3.13 million), Franklin County (\$1.45 million), and Hamilton County (\$822,916). Thus, the most significant impacts were concentrated in 19 Ohio counties. We did not produce estimates for each township and municipality.

Case studies and surveys of Ohio County Engineers provided additional information about the dynamics of this issue. In surveys, most county engineers supported reallocating funds to make up for these impacts, although a few opposed this and others requested more information on the issue. Another potential source of IRP truck impacts is for large, multi-state carriers with large distribution terminals around the state whose trucks are also garaged or domiciled in Ohio. There was no way to include reliable counts of vehicles, unless specific numbers could be obtained from county engineers. Another issue to consider is economic development. Carriers sometimes make requests for improvements to access roadways and other infrastructure enhancements that are expensive for local authorities to build and maintain. This causes an equity issue with the distribution of IRP funds; there is an economic development component as well. The inability to quantify the impacts of lost fees due to multi-state carriers and externalities such as economic development costs means these estimates may understate the total IRP revenue impacts.

Ultimately, if out-of-state IRP registrations belonging to Ohio carriers were to be repatriated to the state, there would be a back-end impact that would reduce the amount of funding available for the excess annual compensation process. Without knowing which carriers could be recruited to return those registrations, the actual direct and indirect impacts could be significantly different from the initial estimates. Any assumptions used as a proxy are potentially tenuous and problematic. Second, these calculations do not speak to any potential impact on state revenues. The study's task was to estimate the impact of IRP jurisdiction shopping on Ohio counties and

local taxing districts – not estimate state-level impacts. There exists the possibility that the state is also losing significant revenue to its Highway Safety Fund because of the difference in how in-state and out-of-state registration fees are assessed. Nevertheless, these issues can be addressed in the long-term solutions that flow out of Phase II of this study, if approved.

5.1 Recommendations for Implementation of Research Findings

If Phase II proceeds, Ohio officials and the research team will need to consult about the potential marketing strategies and tools, as well as long-term state strategies that are available to improve IRP distributions. The technical advisory committee will need to decide: (1) whether to pursue a solution that solely addresses the distribution equity or one that tackles the economic development issue; (2) whether the excess annual compensation funds should be used to remediate problems with equity or if another source of funding is preferable; (3) if a reporting mechanism for domiciled vehicles should be established so that it is easier for Ohio County Engineers to address jurisdiction shopping; (4) on policy solutions that best addresses the issue; and (5) on the general direction for the types of marketing strategies and tools most useful to engineers. The research team has developed an IRP fleet impact estimator, which Ohio County Engineers can use to estimate the impact of a fleet in their county that will be shifting its registrations to another state. The calculator lets users select the county from a drop-down menu before inputting fleet information. The tool estimates the impact on the county, township, and municipalities where the carrier is located. The tool uses the same methodology as the impact assessment in Chapter 3.

References

- Ahlers, David, & Lakonishok, Josef. (1983). A study of economists' consensus forecast. *Management Science*, 29(10). 1113-1125.
- Albritton, Robert B., & Dran, Ellen. (1987). Balanced Budgets and State Surpluses: The Politics of Budgeting in Illinois. *Public Administration Review*, 47(2). 143-152.
- Armstrong, J. Scott. (1978). Forecasting with econometric methods: Folklore vs fact. *Journal of Business*, 51(4). 549-564.
- Armstrong, J. Scott. (1984). Forecasting by extrapolation: Conclusions from 25 years of research. *Interfaces*, 14(6). 52-66.
- Ascher, William. (1981). The forecasting potential of complex models. *Policy Sciences*, 13. 247-267.
- Brandon, Charles H., Jarett, Jeffrey E., & Khumawala, Saleha B. (1983). Revising Forecasts of Accounting Earnings: A Comparison with the Box-Jenkins Method. *Management Science*, 29(2). 256-263.
- Casavant, Ken & Jessup, Eric. (2004). Idaho Commercial Truck Registration Study. National Institute for the Advancement of Transportation Technology, University of Idaho, 2004. Retrieved from www.webs1.uidaho.edu/niatt/research/Final_Reports/KLK480_N04-05.pdf. Accessed 7 February 2012.
- Cirincione, Carmen, Gurrieri, Gustavo, & Van de Sande, Bart. (1999). Municipal Government Revenue Forecasting: Issues of Method and Data. *Public Budgeting and Finance*, 19(1). 24-46.
- Dal Ponte, Gregg. (2010, August). IRP Full Reciprocity Plan. IRP Full Reciprocity Task Force. Retrieved from http://c.ymcdn.com/sites/www.irponline.org/resource/resmgr/about_irp_inc/frp_white_paper.pdf. Accessed 15 March 2014
- Downs, G.W. & Roche, D.M. (1983). Municipal Budget Forecasting with Multivariate ARMA Models. *Journal of Forecasting*, 2(4). 377-387.
- Feenberg, Daniel, Gentry, W., Gilroy, D., & Rosen, H. (1988). Testing the Rationality of State Revenue Forecasts. *National Bureau of Economic Research*, Working Paper No. 2628.
- Frank, Howard A. (1993). *Budgetary Forecasting in Local Government: New Tools and Techniques*. Westport: Quorum Books.
- Frank, Howard A. & Gianakis, Gerasimos. (1990). Raising the Bridge Using Time Series Forecasting Models. *Public Productivity & Management Review*, 14(2). 171-188.

- Grizzle, Gloria & Klay, William E. (1994). Forecasting State Sales Tax Revenues: Comparing the Accuracy of Different Methods. *State and Local Government Review*, 26(3). 142-152.
- Huffenberger, Gary. (2015, April 14). County eyes R and L truck registration funds. *Wilmington News-Journal*. Retrieved from http://wnewsj.com/news/home_top-news/152923214/County-eyes-R-and-L-truck-registration-funds
Accessed 16 April 2015
- Jasek, Debbie, Ojah, Mark, & Hoover, Bruce. (2003, September). Heavy Truck Registration in Texas. *Texas Transportation Institute. FHWA/TX-04/0-4065-1*.
- Karch, Andrew. (2007, March). Emerging Issues and Future Directions in State Policy Diffusion Research. *State Politics & Policy Quarterly*, 7.54.
- Klay, William. (1983). Revenue Forecasting: An Administrative Perspective. In J. Rabin & T.D. Lynch (Eds.), *Handbook of Public Budgeting and Financial Management*. New York: Marcel Dekker.
- Mahmoud, Essam. (1984). Accuracy in forecasting: A survey. *Journal of Forecasting*, 3. 139-159.
- Martin, Andrew, Walton, Jennifer, & Bell, Mark. (2013, January). Motor Carrier Tax Consolidation Study. *Kentucky Transportation Center. KTC-12-18/SPR434-12-1F*.
- Moca, H. Naci, & Azad, Sam. (1995). Accuracy and rationality of state General Fund Revenue forecasts: Evidence from panel data. *International Journal of Forecasting*, 11. 417-427.
- O'Connell, Lenahan, Yusef, Juita-Elana, & Hackbart, Merl. (2007, February). The International Fuel Tax Agreement (IFTA) and International Registration Plan (IRP): Allocating Commercial Fuel Tax and Registration Fee Payments Across Multiple Jurisdictions. *Kentucky Transportation Center. KTC-07-09/TA-05-1F*.
- Rodgers, Robert, & Joyce, Philip. (1996). The Effect of Underforecasting on the Accuracy of Revenue Forecasts by State Governments. *Public Administration Review*, 56(1). 48-56.
- Rubin, Irene S. (1987). Estimated and Actual Urban Revenues: Exploring the Gap. *Public Budgeting and Finance*, (Winter). 83-95.
- Sage, Jeremy, Casavant, Ken, & Lawson, Catherine. (2013, March). Full Reciprocity Financial Impact Study Review: Final Compilation Report. Freight Policy Transportation Institute: Washington State University.
- Schroeder, Larry. (1982). Local Government Multi-Year Budgetary Forecasting: Some Administrative and Political Issues. *Public Administration Review*, 42(2). 121-127.
- Schwartzberg, Eric. (2013, June 28). Tax abatement paves way for new facility, jobs. *The Journal-News*. Accessed 18 April 2015 via LexisNexis Academic.

Zarnowitz, Victor. (1992). The Record and Improvability of Economic Forecasting. In Victor Zarnowitz (*ed.*), *Business Cycles: Theory, History, Indicators, and Forecasting* (519-534). Chicago, IL: University of Chicago Press.

Appendices

Appendix	Description
A	IRP County Revenue, 2009-2014
B	IRP Statewide Taxing Distributions, 2009-2014
C	IRP Annual Excess Compensation, 2009-2014
D	IRP Out-of-State Registration Impact by County, 2015
E	IRP County Revenue Forecast, 2015-2019
F	IRP Case Studies Data for Clinton, Mahoning, Butler, and Franklin County
G	ODPS Impact Estimate for Clinton County
H	ODPS Impact Estimate for Mahoning County
I	State IRP Forecast Output
* Appendices A-H are in an accompanying Excel document.	

Appendix I. State IRP Forecast Output

County Time Trend Estimates

. reg adams year

Source	SS	df	MS	Number of obs = 6		
Model	499968628	1	499968628			F(1, 4) = 139.58
Residual	14327739.3	4	3581934.82			Prob > F = 0.0003
						R-squared = 0.9721
						Adj R-squared = 0.9652
Total	514296367	5	102859273			Root MSE = 1892.6

adams	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	5345.057	452.4179	11.81	0.000	4088.944	6601.171
_cons	114151.5	1761.915	64.79	0.000	109259.6	119043.3

. reg allen year

Source	SS	df	MS	Number of obs = 6		
Model	2.5292e+09	1	2.5292e+09			F(1, 4) = 12.84
Residual	787755973	4	196938993			Prob > F = 0.0231
						R-squared = 0.7625
						Adj R-squared = 0.7031
Total	3.3170e+09	5	663400889			Root MSE = 14033

allen	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	-12022	3354.647	-3.58	0.023	-21335.99	-2708.007
_cons	410265.3	13064.47	31.40	0.000	373992.5	446538.1

. reg ashland year

Source	SS	df	MS	Number of obs = 6		
Model	591882690	1	591882690			F(1, 4) = 5.97
Residual	396585472	4	99146368			Prob > F = 0.0710
						R-squared = 0.5988
						Adj R-squared = 0.4985
Total	988468162	5	197693632			Root MSE = 9957.2

ashland	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	5815.657	2380.232	2.44	0.071	-792.9277	12424.24
_cons	302587.2	9269.674	32.64	0.000	276850.5	328323.9

. reg ashtabula year

Source	SS	df	MS	Number of obs = 6		
Model	477468382	1	477468382			F(1, 4) = 1.57
Residual	1.2161e+09	4	304019918			Prob > F = 0.2784
						R-squared = 0.2819
						Adj R-squared = 0.1024
Total	1.6935e+09	5	338709611			Root MSE = 17436

ashtabula	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	5223.4	4168.041	1.25	0.278	-6348.937	16795.74
_cons	251837.3	16232.19	15.51	0.000	206769.5	296905

. reg athens year

Source	SS	df	MS	Number of obs = 6		
Model	5442176.06	1	5442176.06		F(1, 4) =	1.23
Residual	17718835.9	4	4429708.99		Prob > F =	0.3298
					R-squared =	0.2350
					Adj R-squared =	0.0437
Total	23161012	5	4632202.4		Root MSE =	2104.7

athens	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	557.6571	503.1165	1.11	0.330	-839.2182	1954.533
_cons	97534.2	1959.357	49.78	0.000	92094.15	102974.2

. reg auglaize year

Source	SS	df	MS	Number of obs = 6		
Model	232235786	1	232235786		F(1, 4) =	3.59
Residual	258673961	4	64668490.3		Prob > F =	0.1310
					R-squared =	0.4731
					Adj R-squared =	0.3413
Total	490909747	5	98181949.4		Root MSE =	8041.7

auglaize	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	3642.886	1922.327	1.90	0.131	-1694.351	8980.122
_cons	230533.7	7486.389	30.79	0.000	209748.2	251319.3

. reg belmont year

Source	SS	df	MS	Number of obs = 6		
Model	4.6902e+09	1	4.6902e+09		F(1, 4) =	11.26
Residual	1.6667e+09	4	416679953		Prob > F =	0.0284
					R-squared =	0.7378
					Adj R-squared =	0.6723
Total	6.3569e+09	5	1.2714e+09		Root MSE =	20413

belmont	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	16370.97	4879.578	3.35	0.028	2823.091	29918.85
_cons	303059.9	19003.23	15.95	0.000	250298.5	355821.3

. reg brown year

Source	SS	df	MS	Number of obs = 6		
Model	557796571	1	557796571		F(1, 4) =	4.08
Residual	547101722	4	136775430		Prob > F =	0.1136
					R-squared =	0.5048
					Adj R-squared =	0.3810
Total	1.1049e+09	5	220979659		Root MSE =	11695

```
-----+-----
brown | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
year  | 5645.714 2795.664   2.02  0.114   -2116.294  13407.72
_cons | 150652.7 10887.55  13.84  0.000   120424    180881.3
-----+-----
```

. reg butler year

```
Source | SS   df MS   Number of obs = 6
-----+-----
Model | 7.4195e+09   1 7.4195e+09   Prob > F = 0.5246
Residual | 6.1229e+10   4 1.5307e+10   R-squared   = 0.1081
-----+-----
Total | 6.8648e+10   5 1.3730e+10   Adj R-squared = -0.1149
Root MSE = 1.2e+05
```

```
-----+-----
butler | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
year  | 20590.63 29575.24   0.70  0.525   -61523.41  102704.7
_cons | 908417.1 115179    7.89  0.001    588628.9  1228205
-----+-----
```

. reg carroll year

```
Source | SS   df MS   Number of obs = 6
-----+-----
Model | 55345586.4   1 55345586.4   Prob > F = 0.0761
Residual | 39135790.4   4 9783947.6   R-squared   = 0.5858
-----+-----
Total | 94481376.8   5 18896275.4   Adj R-squared = 0.4822
Root MSE = 3127.9
```

```
-----+-----
carroll | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
year  | 1778.371 747.7183   2.38  0.076   -297.6275  3854.37
_cons | 159470.5 2911.945  54.76  0.000    151385.7  167555.4
-----+-----
```

. reg champaign year

```
Source | SS   df MS   Number of obs = 6
-----+-----
Model | 247686318   1 247686318   Prob > F = 0.0166
Residual | 62956615.8   4 15739153.9   R-squared   = 0.7973
-----+-----
Total | 310642934   5 62128586.8   Adj R-squared = 0.7467
Root MSE = 3967.3
```

```
-----+-----
champaign | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
year  | 3762.114 948.3566   3.97  0.017    1129.054  6395.174
_cons | 116858.6 3693.318  31.64  0.000    106604.3  127112.9
-----+-----
```

. reg clark year

```
Source | SS   df MS   Number of obs = 6
-----+-----
Model | 2.2994e+10   1 2.2994e+10   Prob > F = 0.0227
Residual | 7.0776e+09   4 1.7694e+09   R-squared   = 0.7646
-----+-----
Total | 3.0072e+10   5 6.0144e+09   Adj R-squared = 0.7058
Root MSE = 42064
```

```
-----
```

clark	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	-36248.74	10055.26	-3.60	0.023	-64166.63	-8330.857
_cons	409028.3	39159.62	10.45	0.000	300303.7	517752.8

```
-----
```

. reg clermont year

```
-----
```

Source	SS	df	MS	Number of obs = 6		
Model	3.9958e+09	1	3.9958e+09	F(1, 4) =	14.21	
Residual	1.1251e+09	4	281273172	Prob > F =	0.0196	
				R-squared	= 0.7803	
				Adj R-squared	= 0.7254	
Total	5.1209e+09	5	1.0242e+09	Root MSE =	16771	

```
-----
```

```
-----
```

clermont	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	15110.66	4009.084	3.77	0.020	3979.656	26241.66
_cons	375817.5	15613.14	24.07	0.000	332468.5	419166.6

```
-----
```

. reg clinton year

```
-----
```

Source	SS	df	MS	Number of obs = 6		
Model	84229854.2	1	84229854.2	F(1, 4) =	2.39	
Residual	141213529	4	35303382.3	Prob > F =	0.1973	
				R-squared	= 0.3736	
				Adj R-squared	= 0.2170	
Total	225443383	5	45088676.7	Root MSE =	5941.7	

```
-----
```

```
-----
```

clinton	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	2193.886	1420.33	1.54	0.197	-1749.581	6137.353
_cons	148097.7	5531.389	26.77	0.000	132740.1	163455.3

```
-----
```

. reg columbiana year

```
-----
```

Source	SS	df	MS	Number of obs = 6		
Model	2.0986e+09	1	2.0986e+09	F(1, 4) =	2.03	
Residual	4.1323e+09	4	1.0331e+09	Prob > F =	0.2272	
				R-squared	= 0.3368	
				Adj R-squared	= 0.1710	
Total	6.2308e+09	5	1.2462e+09	Root MSE =	32141	

```
-----
```

```
-----
```

columbiana	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	10950.74	7683.248	1.43	0.227	-10381.37	32282.86
_cons	577264.1	29921.95	19.29	0.000	494187.4	660340.7

```
-----
```

. reg coshocton year

```
-----
```

Source	SS	df	MS	Number of obs = 6		
Model	33748.1286	1	33748.1286	F(1, 4) =	0.00	
Residual	318397821	4	79599455.3	Prob > F =	0.9846	
				R-squared	= 0.0001	
				Adj R-squared	= -0.2499	

```
-----
```

Total | 318431570 5 63686313.9 Root MSE = 8921.9

coshocton	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	-43.91429	2132.731	-0.02	0.985	-5965.324	5877.495
_cons	166602.2	8305.793	20.06	0.000	143541.6	189662.8

. reg crawford year

Source	SS	df	MS	Number of obs = 6		F(1, 4) = 6.41
Model	50517216.5	1	50517216.5	Prob > F = 0.0645		
Residual	31500461.5	4	7875115.37	R-squared = 0.6159		
Total	82017678	5	16403535.6	Adj R-squared = 0.5199	Root MSE = 2806.3	

crawford	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	1699.029	670.8253	2.53	0.064	-163.4811	3561.538
_cons	96678.4	2612.489	37.01	0.000	89424.97	103931.8

. reg cuyahoga year

Source	SS	df	MS	Number of obs = 6		F(1, 4) = 130.87
Model	1.8159e+11	1	1.8159e+11	Prob > F = 0.0003		
Residual	5.5499e+09	4	1.3875e+09	R-squared = 0.9703		
Total	1.8714e+11	5	3.7427e+10	Adj R-squared = 0.9629	Root MSE = 37249	

cuyahoga	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	101864.3	8904.199	11.44	0.000	77142.24	126586.3
_cons	1083952	34676.87	31.26	0.000	987673.5	1180230

. reg darke year

Source	SS	df	MS	Number of obs = 6		F(1, 4) = 53.10
Model	3.9499e+09	1	3.9499e+09	Prob > F = 0.0019		
Residual	297521781	4	74380445.3	R-squared = 0.9300		
Total	4.2475e+09	5	849493320	Adj R-squared = 0.9124	Root MSE = 8624.4	

darke	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	15023.69	2061.628	7.29	0.002	9299.688	20747.68
_cons	493104.9	8028.889	61.42	0.000	470813.2	515396.7

. reg defiance year

Source	SS	df	MS	Number of obs = 6		F(1, 4) = 48.29
Model	2.6429e+10	1	2.6429e+10	Prob > F = 0.0023		
Residual	2.1890e+09	4	547253537	R-squared = 0.9235		

```
-----+-----
Total | 2.8618e+10      5  5.7236e+09      Root MSE = 23393
Adj R-squared = 0.9044
```

```
-----+-----
defiance | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
year | 38861.77  5592.104   6.95  0.002  23335.6   54387.94
_cons | 110381.8  21778.12   5.07  0.007   49916.05  170847.5
```

```
. reg delaware year
```

```
Source | SS   df MS         Number of obs = 6
-----+-----
Model | 141591388      1  141591388      F( 1,      4) = 16.56
Residual | 34210465.7     4  8552616.42     Prob > F = 0.0152
Total | 175801853     5  35160370.7     R-squared = 0.8054
Adj R-squared = 0.7568
Root MSE = 2924.5
```

```
-----+-----
delaware | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
year | 2844.457  699.0858   4.07  0.015   903.4838   4785.43
_cons | 153700.1  2722.548  56.45  0.000  146141.1   161259.1
```

```
. reg erie year
```

```
Source | SS   df MS         Number of obs = 6
-----+-----
Model | 1.0666e+09      1  1.0666e+09      F( 1,      4) = 55.00
Residual | 77575811.1     4  19393952.8     Prob > F = 0.0018
Total | 1.1442e+09     5  228843779     R-squared = 0.9322
Adj R-squared = 0.9153
Root MSE = 4403.9
```

```
-----+-----
erie | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
year | 7807.114  1052.723   7.42  0.002   4884.286   10729.94
_cons | 130542.3  4099.767  31.84  0.000  119159.5   141925
```

```
. reg fairfield year
```

```
Source | SS   df MS         Number of obs = 6
-----+-----
Model | 528484375      1  528484375      F( 1,      4) = 25.33
Residual | 83447016.4     4  20861754.1     Prob > F = 0.0073
Total | 611931391     5  122386278     R-squared = 0.8636
Adj R-squared = 0.8295
Root MSE = 4567.5
```

```
-----+-----
fairfield | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
year | 5495.371  1091.833   5.03  0.007   2463.956   8526.787
_cons | 170652.5  4252.08  40.13  0.000  158846.9   182458.2
```

```
. reg fayette year
```

```
Source | SS   df MS         Number of obs = 6
-----+-----
Model | 83433172.6      1  83433172.6     F( 1,      4) = 5.92
Prob > F = 0.0718
```

Residual		56416333.4	4	14104083.3	R-squared	=	0.5966

Total		139849506	5	27969901.2	Adj R-squared	=	0.4957
					Root MSE	=	3755.5

fayette		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	

year		2183.486	897.7459	2.43	0.072	-309.0564	4676.028
_cons		134243.8	3496.218	38.40	0.000	124536.7	143950.9

. reg franklin year

Source		SS	df	MS	Number of obs =	6	F(1, 4) =	14.96

Model		2.6682e+11	1	2.6682e+11	Prob > F =	0.0180	R-squared	= 0.7890
Residual		7.1343e+10	4	1.7836e+10	Adj R-squared	=	0.7363	

Total		3.3816e+11	5	6.7633e+10	Root MSE	=	1.3e+05	

franklin		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	

year		123478.6	31924.58	3.87	0.018	34841.74	212115.5
_cons		1984039	124328.4	15.96	0.000	1638848	2329230

. reg fulton year

Source		SS	df	MS	Number of obs =	6	F(1, 4) =	2.59

Model		776469440	1	776469440	Prob > F =	0.1829	R-squared	= 0.3929
Residual		1.1997e+09	4	299930637	Adj R-squared	=	0.2411	

Total		1.9762e+09	5	395238397	Root MSE	=	17319	

fulton		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	

year		6661.057	4139.915	1.61	0.183	-4833.189	18155.3
_cons		314469.5	16122.65	19.50	0.000	269705.8	359233.1

. reg gallia year

Source		SS	df	MS	Number of obs =	6	F(1, 4) =	2.38

Model		69944011.2	1	69944011.2	Prob > F =	0.1979	R-squared	= 0.3728
Residual		117655449	4	29413862.2	Adj R-squared	=	0.2160	

Total		187599460	5	37519892	Root MSE	=	5423.5	

gallia		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	

year		1999.2	1296.454	1.54	0.198	-1600.332	5598.732
_cons		201691.8	5048.962	39.95	0.000	187673.6	215710

. reg geauga year

Source		SS	df	MS	Number of obs =	6	F(1, 4) =	15.79

```

Model | 4.3065e+10    1  4.3065e+10    Prob > F = 0.0165
Residual | 1.0907e+10    4  2.7267e+09    R-squared   = 0.7979
-----+-----
Total | 5.3971e+10    5  1.0794e+10    Root MSE = 52218
Adj R-squared = 0.7474

```

```

-----+-----
geauga | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
year   | -49606.8 12482.49  -3.97  0.016   -84263.74 -14949.86
_cons  | 482052.8  48612.3   9.92  0.001   347083.4  617022.2
-----+-----

```

. reg greene year

```

Source | SS   df MS   Number of obs = 6
-----+-----
Model | 5.1971e+09    1  5.1971e+09    Prob > F = 0.0285
Residual | 1.8514e+09    4  462854289    R-squared   = 0.7373
-----+-----
Total | 7.0485e+09    5  1.4097e+09    Root MSE = 21514
Adj R-squared = 0.6717

```

```

-----+-----
greene | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
year   | -17233   5142.841  -3.35  0.029   -31511.82 -2954.183
_cons  | 256533   20028.49  12.81  0.000   200925 312141
-----+-----

```

. reg guernsey year

```

Source | SS   df MS   Number of obs = 6
-----+-----
Model | 1.1246e+09    1  1.1246e+09    Prob > F = 0.0036
Residual | 120131657    4  30032914.3    R-squared   = 0.9035
-----+-----
Total | 1.2448e+09    5  248950483    Root MSE = 5480.2
Adj R-squared = 0.8794

```

```

-----+-----
guernsey | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
year   | 8016.486 1310.025   6.12  0.004   4379.272  11653.7
_cons  | 135081.8 5101.816  26.48  0.000   120916.9 149246.7
-----+-----

```

. reg hamilton year

```

Source | SS   df MS   Number of obs = 6
-----+-----
Model | 1.2963e+11    1  1.2963e+11    Prob > F = 0.0026
Residual | 1.1603e+10    4  2.9007e+09    R-squared   = 0.9178
-----+-----
Total | 1.4123e+11    5  2.8246e+10    Root MSE = 53858
Adj R-squared = 0.8973

```

```

-----+-----
hamilton | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
year   | 86065.17 12874.49   6.68  0.003   50319.86 121810.5
_cons  | 1540167 50138.93  30.72  0.000 1400959 1679375
-----+-----

```

. reg hancock year

```

Source | SS   df MS   Number of obs = 6

```

```

-----+-----
Model | 341294977 1 341294977 Prob > F = 0.2816 F( 1, 4) = 1.55
Residual | 882739141 4 220684785 R-squared = 0.2788
-----+-----
Total | 1.2240e+09 5 244806823 Root MSE = 0.0985 Adj R-squared = 0.0985

```

```

-----+-----
 Hancock | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
 year | 4416.171 3551.135 1.24 0.282 -5443.36 14275.7
 _cons | 313111.7 13829.68 22.64 0.000 274714.4 351509.1
-----+-----

```

. reg hardin year

```

Source | SS df MS Number of obs = 6
-----+-----
Model | 486262929 1 486262929 Prob > F = 0.0004 F( 1, 4) = 125.16
Residual | 15541038.6 4 3885259.64 R-squared = 0.9690
-----+-----
Total | 501803968 5 100360794 Root MSE = 0.9613 Adj R-squared = 0.9613

```

```

-----+-----
 hardin | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
 year | 5271.286 471.1845 11.19 0.000 3963.068 6579.504
 _cons | 153509 1835 83.66 0.000 148414.2 158603.8
-----+-----

```

. reg harrison year

```

Source | SS df MS Number of obs = 6
-----+-----
Model | 279644113 1 279644113 Prob > F = 0.0089 F( 1, 4) = 22.70
Residual | 49271988.3 4 12317997.1 R-squared = 0.8502
-----+-----
Total | 328916102 5 65783220.3 Root MSE = 0.8127 Adj R-squared = 0.8127

```

```

-----+-----
 harrison | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
 year | 3997.457 838.9789 4.76 0.009 1668.078 6326.836
 _cons | 94103.4 3267.353 28.80 0.000 85031.77 103175
-----+-----

```

. reg henry year

```

Source | SS df MS Number of obs = 6
-----+-----
Model | 202136833 1 202136833 Prob > F = 0.2405 F( 1, 4) = 1.90
Residual | 426317904 4 106579476 R-squared = 0.3216
-----+-----
Total | 628454737 5 125690947 Root MSE = 0.1521 Adj R-squared = 0.1521

```

```

-----+-----
 henry | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
 year | 3398.629 2467.844 1.38 0.241 -3453.206 10250.46
 _cons | 303845.1 9610.873 31.61 0.000 277161.1 330529.2
-----+-----

```

. reg highland year

```

Source | SS df MS      Number of obs = 6
-----+-----
Model | 490526160 1 490526160  Prob > F = 0.0002
Residual | 12590137.9 4 3147534.49  R-squared = 0.9750
-----+-----
Total | 503116298 5 100623260  Root MSE = 1774.1
Adj R-squared = 0.9687
F( 1, 4) = 155.84

```

```

-----+-----
highland | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
year | 5294.343 424.098 12.48 0.000 4116.858 6471.828
_cons | 137619.8 1651.624 83.32 0.000 133034.2 142205.4
-----+-----

```

. reg hocking year

```

Source | SS df MS      Number of obs = 6
-----+-----
Model | 91282344.2 1 91282344.2  Prob > F = 0.1172
Residual | 92040949.1 4 23010237.3  R-squared = 0.4979
-----+-----
Total | 183323293 5 36664658.7  Root MSE = 4796.9
Adj R-squared = 0.3724
F( 1, 4) = 3.97

```

```

-----+-----
hocking | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
year | 2283.886 1146.678 1.99 0.117 -899.8031 5467.575
_cons | 90746.07 4465.67 20.32 0.000 78347.38 103144.8
-----+-----

```

. reg holmes year

```

Source | SS df MS      Number of obs = 6
-----+-----
Model | 4.9014e+09 1 4.9014e+09  Prob > F = 0.0014
Residual | 310204502 4 77551125.4  R-squared = 0.9405
-----+-----
Total | 5.2116e+09 5 1.0423e+09  Root MSE = 8806.3
Adj R-squared = 0.9256
F( 1, 4) = 63.20

```

```

-----+-----
holmes | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
year | 16735.57 2105.111 7.95 0.001 10890.85 22580.3
_cons | 256419.3 8198.23 31.28 0.000 233657.4 279181.3
-----+-----

```

. reg huron year

```

Source | SS df MS      Number of obs = 6
-----+-----
Model | 103622689 1 103622689  Prob > F = 0.3046
Residual | 299413302 4 74853325.6  R-squared = 0.2571
-----+-----
Total | 403035991 5 80607198.3  Root MSE = 8651.8
Adj R-squared = 0.0714
F( 1, 4) = 1.38

```

```

-----+-----
huron | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
year | 2433.371 2068.171 1.18 0.305 -3308.793 8175.536
_cons | 283729.5 8054.37 35.23 0.000 261367 306092.1
-----+-----

```

. reg jackson year

```

Source | SS df MS      Number of obs = 6
-----+-----
Model | 130991472    1 130991472    Prob > F = 0.2060
Residual | 230406593    4 57601648.2    R-squared = 0.3625
-----+-----
Total | 361398065    5 72279613    Adj R-squared = 0.2031
Root MSE = 7589.6

```

```

-----+-----
jackson | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
year | 2735.914 1814.255   1.51  0.206   -2301.266  7773.095
_cons | 159807.1 7065.51   22.62  0.000   140190.1  179424.1
-----+-----

```

. reg jefferson year

```

Source | SS df MS      Number of obs = 6
-----+-----
Model | 5.6134e+09    1 5.6134e+09    Prob > F = 0.0100
Residual | 1.0567e+09    4 264179493    R-squared = 0.8416
-----+-----
Total | 6.6701e+09    5 1.3340e+09    Adj R-squared = 0.8020
Root MSE = 16254

```

```

-----+-----
jefferson | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
year | 17909.91 3885.353   4.61  0.010   7122.444  28697.38
_cons | 145082.5 15131.28   9.59  0.001   103071.3  187093.6
-----+-----

```

. reg knox year

```

Source | SS df MS      Number of obs = 6
-----+-----
Model | 758819183    1 758819183    Prob > F = 0.0000
Residual | 5155693.37    4 1288923.34    R-squared = 0.9933
-----+-----
Total | 763974876    5 152794975    Adj R-squared = 0.9916
Root MSE = 1135.3

```

```

-----+-----
knox | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
year | 6584.914 271.3904  24.26  0.000   5831.414  7338.415
_cons | 182834.8 1056.914  172.99  0.000   179900.3  185769.3
-----+-----

```

. reg lake year

```

Source | SS df MS      Number of obs = 6
-----+-----
Model | 1251833.16    1 1251833.16    Prob > F = 0.6768
Residual | 24848997.7    4 6212249.42    R-squared = 0.0480
-----+-----
Total | 26100830.8    5 5220166.17    Adj R-squared = -0.1900
Root MSE = 2492.4

```

```

-----+-----
lake | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
year | -267.4571 595.8067  -0.45  0.677   -1921.682  1386.768
_cons | 148024.9 2320.334  63.79  0.000   141582.7  154467.2
-----+-----

```

. reg lawrence year

Source	SS	df	MS	Number of obs = 6		
Model	484319770	1	484319770			F(1, 4) = 5.77
Residual	335530336	4	83882583.9			Prob > F = 0.0741
						R-squared = 0.5907
						Adj R-squared = 0.4884
Total	819850105	5	163970021			Root MSE = 9158.7

lawrence	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	-5260.743	2189.358	-2.40	0.074	-11339.38	817.8908
_cons	243804.9	8526.326	28.59	0.000	220132.1	267477.8

. reg licking year

Source	SS	df	MS	Number of obs = 6		
Model	248876573	1	248876573			F(1, 4) = 6.98
Residual	142520894	4	35630223.6			Prob > F = 0.0574
						R-squared = 0.6359
						Adj R-squared = 0.5448
Total	391397467	5	78279493.5			Root MSE = 5969.1

licking	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	3771.143	1426.889	2.64	0.057	-190.5367	7732.822
_cons	304396.7	5556.935	54.78	0.000	288968.1	319825.2

. reg logan year

Source	SS	df	MS	Number of obs = 6		
Model	2.1357e+09	1	2.1357e+09			F(1, 4) = 7.94
Residual	1.0760e+09	4	268996963			Prob > F = 0.0479
						R-squared = 0.6650
						Adj R-squared = 0.5812
Total	3.2117e+09	5	642341977			Root MSE = 16401

logan	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	11047.23	3920.619	2.82	0.048	161.8445	21932.61
_cons	106140.2	15268.62	6.95	0.002	63747.72	148532.7

. reg lorain year

Source	SS	df	MS	Number of obs = 6		
Model	3.5302e+09	1	3.5302e+09			F(1, 4) = 100.16
Residual	140988387	4	35247096.8			Prob > F = 0.0006
						R-squared = 0.9616
						Adj R-squared = 0.9520
Total	3.6712e+09	5	734241590			Root MSE = 5936.9

lorain	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	14203.06	1419.197	10.01	0.001	10262.73	18143.38
_cons	240165.1	5526.978	43.45	0.000	224819.8	255510.5

. reg lucas year

Source		SS	df	MS	Number of obs = 6				
-----+									
Model		8.2714e+09	1	8.2714e+09		F(1, 4) =	31.79		
Residual		1.0408e+09	4	260204031		Prob > F =	0.0049		
-----+									
Total		9.3122e+09	5	1.8624e+09		R-squared =	0.8882		
-----+									
						Adj R-squared =	0.8603		
						Root MSE =	16131		

lucas		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
-----+							
year		21740.57	3856.009	5.64	0.005	11034.58	32446.57
_cons		734220.7	15017	48.89	0.000	692526.8	775914.5

. reg madison year

Source		SS	df	MS	Number of obs = 6				
-----+									
Model		2.8075e+09	1	2.8075e+09		F(1, 4) =	62.28		
Residual		180305093	4	45076273.3		Prob > F =	0.0014		
-----+									
Total		2.9878e+09	5	597557465		R-squared =	0.9397		
-----+									
						Adj R-squared =	0.9246		
						Root MSE =	6713.9		

madison		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
-----+							
year		12666	1604.926	7.89	0.001	8210.011	17121.99
_cons		174853.3	6250.288	27.98	0.000	157499.8	192206.9

. reg mahoning year

Source		SS	df	MS	Number of obs = 6				
-----+									
Model		3.4983e+11	1	3.4983e+11		F(1, 4) =	11.95		
Residual		1.1712e+11	4	2.9279e+10		Prob > F =	0.0259		
-----+									
Total		4.6694e+11	5	9.3389e+10		R-squared =	0.7492		
-----+									
						Adj R-squared =	0.6865		
						Root MSE =	1.7e+05		

mahoning		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
-----+							
year		141386.6	40903.2	3.46	0.026	27821.11	254952.1
_cons		1063837	159295.1	6.68	0.003	621563.3	1506111

. reg marion year

Source		SS	df	MS	Number of obs = 6				
-----+									
Model		475709719	1	475709719		F(1, 4) =	37.89		
Residual		50225856.4	4	12556464.1		Prob > F =	0.0035		
-----+									
Total		525935575	5	105187115		R-squared =	0.9045		
-----+									
						Adj R-squared =	0.8806		
						Root MSE =	3543.5		

marion		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
-----+							
year		5213.771	847.0609	6.16	0.004	2861.953	7565.59
_cons		129320.5	3298.828	39.20	0.000	120161.5	138479.5

. reg medina year

Source		SS	df	MS	Number of obs = 6				
-----+									
Model		1.0140e+10	1	1.0140e+10		F(1, 4) =	122.13		
Residual		332101909	4	83025477.3		Prob > F =	0.0004		
-----+									
Total		1.0472e+10	5	2.0944e+09		R-squared =	0.9683		
-----+									
						Adj R-squared =	0.9604		
						Root MSE =	9111.8		

medina		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]			
-----+									
year		24071.37	2178.144	11.05	0.000	18023.87	30118.87		
_cons		330884.2	8482.654	39.01	0.000	307332.6	354435.8		

. reg meigs year

Source		SS	df	MS	Number of obs = 6				
-----+									
Model		146555054	1	146555054		F(1, 4) =	20.47		
Residual		28644231.1	4	7161057.78		Prob > F =	0.0106		
-----+									
Total		175199285	5	35039857.1		R-squared =	0.8365		
-----+									
						Adj R-squared =	0.7956		
						Root MSE =	2676		

meigs		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]			
-----+									
year		2893.886	639.69	4.52	0.011	1117.822	4669.95		
_cons		99286.73	2491.235	39.85	0.000	92369.96	106203.5		

. reg mercer year

Source		SS	df	MS	Number of obs = 6				
-----+									
Model		2.5076e+10	1	2.5076e+10		F(1, 4) =	31.35		
Residual		3.1991e+09	4	799773977		Prob > F =	0.0050		
-----+									
Total		2.8275e+10	5	5.6549e+09		R-squared =	0.8869		
-----+									
						Adj R-squared =	0.8586		
						Root MSE =	28280		

mercer		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]			
-----+									
year		37853.49	6760.279	5.60	0.005	19083.94	56623.03		
_cons		422178.5	26327.5	16.04	0.000	349081.6	495275.3		

. reg miami year

Source		SS	df	MS	Number of obs = 6				
-----+									
Model		2.9111e+09	1	2.9111e+09		F(1, 4) =	24.71		
Residual		471311412	4	117827853		Prob > F =	0.0076		
-----+									
Total		3.3824e+09	5	676475423		R-squared =	0.8607		
-----+									
						Adj R-squared =	0.8258		
						Root MSE =	10855		

miami		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]			
-----+									
year		12897.54	2594.806	4.97	0.008	5693.205	20101.88		

```

_cons | 274746.3 10105.32 27.19 0.000 246689.4 302803.1
-----

```

```
. reg monroe year
```

```

Source | SS df MS Number of obs = 6
-----+-----
Model | 278194919 1 278194919 F( 1, 4) = 12.86
Residual | 86515880.7 4 21628970.2 Prob > F = 0.0230
Total | 364710799 5 72942159.9 R-squared = 0.7628
Adj R-squared = 0.7035
Root MSE = 4650.7
-----

```

```

monroe | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
year | 3987.086 1111.729 3.59 0.023 900.4314 7073.74
_cons | 111691.5 4329.562 25.80 0.000 99670.74 123712.3
-----

```

```
. reg montgomery year
```

```

Source | SS df MS Number of obs = 6
-----+-----
Model | 3.0471e+10 1 3.0471e+10 F( 1, 4) = 40.05
Residual | 3.0434e+09 4 760848338 Prob > F = 0.0032
Total | 3.3515e+10 5 6.7030e+09 R-squared = 0.9092
Adj R-squared = 0.8865
Root MSE = 27583
-----

```

```

montgomery | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
year | 41727.97 6593.713 6.33 0.003 23420.89 60035.05
_cons | 723583.9 25678.82 28.18 0.000 652288.1 794879.8
-----

```

```
. reg morgan year
```

```

Source | SS df MS Number of obs = 6
-----+-----
Model | 203573598 1 203573598 F( 1, 4) = 141.79
Residual | 5743089.1 4 1435772.28 Prob > F = 0.0003
Total | 209316687 5 41863337.5 R-squared = 0.9726
Adj R-squared = 0.9657
Root MSE = 1198.2
-----

```

```

morgan | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
year | 3410.686 286.4335 11.91 0.000 2615.419 4205.953
_cons | 77858.27 1115.498 69.80 0.000 74761.15 80955.39
-----

```

```
. reg morrow year
```

```

Source | SS df MS Number of obs = 6
-----+-----
Model | 84966409.2 1 84966409.2 F( 1, 4) = 4.52
Residual | 75191685.7 4 18797921.4 Prob > F = 0.1007
Total | 160158095 5 32031619 R-squared = 0.5305
Adj R-squared = 0.4131
Root MSE = 4335.7
-----

```

```

morrow | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----

```

year		2203.457	1036.42	2.13	0.101	-674.1068	5081.021
_cons		123672.7	4036.277	30.64	0.000	112466.2	134879.2

. reg muskingum year

Source		SS	df	MS	Number of obs = 6		
-----+							
Model		1.1672e+09	1	1.1672e+09		F(1, 4) =	5.13
Residual		909638126	4	227409531		Prob > F =	0.0862
-----+							
Total		2.0768e+09	5	415357636		R-squared =	0.5620
-----+							
						Adj R-squared =	0.4525
						Root MSE =	15080

muskingum		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
-----+						
year		8166.657	3604.834	2.27	0.086	-1841.967 18175.28
_cons		244276.2	14038.81	17.40	0.000	205298.2 283254.2

. reg noble year

Source		SS	df	MS	Number of obs = 6		
-----+							
Model		738861589	1	738861589		F(1, 4) =	54.72
Residual		54005836.3	4	13501459.1		Prob > F =	0.0018
-----+							
Total		792867426	5	158573485		R-squared =	0.9319
-----+							
						Adj R-squared =	0.9149
						Root MSE =	3674.4

noble		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
-----+						
year		6497.743	878.3575	7.40	0.002	4059.031 8936.454
_cons		103013.4	3420.711	30.11	0.000	93515.98 112510.8

. reg ottawa year

Source		SS	df	MS	Number of obs = 6		
-----+							
Model		184450709	1	184450709		F(1, 4) =	13.92
Residual		53011205.7	4	13252801.4		Prob > F =	0.0203
-----+							
Total		237461915	5	47492383		R-squared =	0.7768
-----+							
						Adj R-squared =	0.7209
						Root MSE =	3640.4

ottawa		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
-----+						
year		3246.543	870.2315	3.73	0.020	830.3927 5662.693
_cons		130430.9	3389.065	38.49	0.000	121021.4 139840.5

. reg paulding year

Source		SS	df	MS	Number of obs = 6		
-----+							
Model		680197978	1	680197978		F(1, 4) =	5.95
Residual		457463772	4	114365943		Prob > F =	0.0713
-----+							
Total		1.1377e+09	5	227532350		R-squared =	0.5979
-----+							
						Adj R-squared =	0.4974
						Root MSE =	10694

paulding		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
----------	--	-------	-----------	---	------	----------------------

```

-----+-----
year | 6234.457 2556.403 2.44 0.071 -863.2557 13332.17
_cons | 122272.4 9955.76 12.28 0.000 94630.78 149914
-----+-----

```

. reg perry year

```

Source | SS df MS Number of obs = 6
-----+-----
Model | 14361912.1 1 14361912.1 F( 1, 4) = 9.88
Residual | 5815302.7 4 1453825.68 Prob > F = 0.0347
Total | 20177214.8 5 4035442.97 R-squared = 0.7118
Adj R-squared = 0.6397
Root MSE = 1205.7
-----+-----

```

```

-----+-----
perry | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
year | 905.9143 288.2286 3.14 0.035 105.6633 1706.165
_cons | 102685.1 1122.489 91.48 0.000 99568.6 105801.7
-----+-----

```

. reg pickaway year

```

Source | SS df MS Number of obs = 6
-----+-----
Model | 630610.514 1 630610.514 F( 1, 4) = 0.05
Residual | 55839196.8 4 13959799.2 Prob > F = 0.8421
Total | 56469807.3 5 11293961.5 R-squared = 0.0112
Adj R-squared = -0.2360
Root MSE = 3736.3
-----+-----

```

```

-----+-----
pickaway | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
year | -189.8286 893.1421 -0.21 0.842 -2669.589 2289.931
_cons | 125666.1 3478.289 36.13 0.000 116008.8 135323.3
-----+-----

```

. reg pike year

```

Source | SS df MS Number of obs = 6
-----+-----
Model | 880017920 1 880017920 F( 1, 4) = 82.42
Residual | 42709315.1 4 10677328.8 Prob > F = 0.0008
Total | 922727235 5 184545447 R-squared = 0.9537
Adj R-squared = 0.9421
Root MSE = 3267.6
-----+-----

```

```

-----+-----
pike | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
year | 7091.314 781.1102 9.08 0.001 4922.605 9260.024
_cons | 126897.1 3041.987 41.72 0.000 118451.2 135343
-----+-----

```

. reg portage year

```

Source | SS df MS Number of obs = 6
-----+-----
Model | 1.1864e+10 1 1.1864e+10 F( 1, 4) = 73.82
Residual | 642828439 4 160707110 Prob > F = 0.0010
Total | 1.2507e+10 5 2.5014e+09 R-squared = 0.9486
Adj R-squared = 0.9358
Root MSE = 12677
-----+-----

```

	portage	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year		26037.51	3030.39	8.59	0.001	17623.8	34451.23
_cons		464775.5	11801.67	39.38	0.000	432008.8	497542.2

. reg preble year

Source	SS	df	MS	Number of obs = 6			
Model		152273101	1	152273101	Prob > F =	0.1968	F(1, 4) = 2.39
Residual		254503778	4	63625944.5	R-squared =	0.3743	
Total		406776879	5	81355375.8	Adj R-squared =	0.2179	Root MSE = 7976.6

	preble	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year		2949.8	1906.769	1.55	0.197	-2344.24	8243.84
_cons		256632.5	7425.799	34.56	0.000	236015.2	277249.9

. reg putnam year

Source	SS	df	MS	Number of obs = 6			
Model		379990381	1	379990381	Prob > F =	0.0742	F(1, 4) = 5.77
Residual		263504818	4	65876204.5	R-squared =	0.5905	
Total		643495199	5	128699040	Adj R-squared =	0.4881	Root MSE = 8116.4

	putnam	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year		4659.8	1940.194	2.40	0.074	-727.0434	10046.64
_cons		199341.5	7555.972	26.38	0.000	178362.8	220320.3

. reg richland year

Source	SS	df	MS	Number of obs = 6			
Model		12260794.5	1	12260794.5	Prob > F =	0.4661	F(1, 4) = 0.65
Residual		75731832.8	4	18932958.2	R-squared =	0.1393	
Total		87992627.3	5	17598525.5	Adj R-squared =	-0.0758	Root MSE = 4351.2

	richland	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year		837.0286	1040.136	0.80	0.466	-2050.853	3724.91
_cons		196594.7	4050.749	48.53	0.000	185348.1	207841.4

. reg ross year

Source	SS	df	MS	Number of obs = 6			
Model		391483181	1	391483181	Prob > F =	0.0442	F(1, 4) = 8.40
Residual		186327430	4	46581857.6	R-squared =	0.6775	
Total		577810612	5	115562122	Adj R-squared =	0.5969	Root MSE = 6825.1

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```

ross	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	4729.743	1631.509	2.90	0.044	199.9487	9259.537
_cons	173096.4	6353.813	27.24	0.000	155455.4	190737.4

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```

. reg sandusky year

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```

Source	SS	df	MS	Number of obs = 6		
Model	146144411	1	146144411	F(1, 4) =	3.30	
Residual	177219555	4	44304888.7	Prob > F =	0.1435	
				R-squared	= 0.4520	
				Adj R-squared	= 0.3149	
Total	323363965	5	64672793.1	Root MSE =	6656.2	

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sandusky	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	2889.829	1591.134	1.82	0.144	-1527.868	7307.525
_cons	203954.9	6196.577	32.91	0.000	186750.5	221159.4

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```

. reg scioto year

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```

Source	SS	df	MS	Number of obs = 6		
Model	37758441.7	1	37758441.7	F(1, 4) =	2.27	
Residual	66613611.8	4	16653402.9	Prob > F =	0.2066	
				R-squared	= 0.3618	
				Adj R-squared	= 0.2022	
Total	104372054	5	20874410.7	Root MSE =	4080.9	

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scioto	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	1468.886	975.5117	1.51	0.207	-1239.569	4177.34
_cons	265455.4	3799.072	69.87	0.000	254907.5	276003.3

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. reg seneca year

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```

Source	SS	df	MS	Number of obs = 6		
Model	98812.8571	1	98812.8571	F(1, 4) =	0.00	
Residual	170624579	4	42656144.8	Prob > F =	0.9639	
				R-squared	= 0.0006	
				Adj R-squared	= -0.2493	
Total	170723392	5	34144678.4	Root MSE =	6531.2	

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```

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```

seneca	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	-75.14286	1561.248	-0.05	0.964	-4409.861	4259.575
_cons	227742	6080.186	37.46	0.000	210860.7	244623.3

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```

. reg shelby year

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```

Source	SS	df	MS	Number of obs = 6		
Model	1.6139e+09	1	1.6139e+09	F(1, 4) =	8.62	
Residual	748928060	4	187232015	Prob > F =	0.0426	
				R-squared	= 0.6830	
				Adj R-squared	= 0.6038	
Total	2.3629e+09	5	472572212	Root MSE =	13683	

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shelby	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	-9603.371	3270.928	-2.94	0.043	-18684.92	-521.8184
_cons	569175.5	12738.44	44.68	0.000	533807.9	604543

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```

. reg stark year

```
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```

Source	SS	df	MS	Number of obs = 6		
Model	3.9194e+09	1	3.9194e+09	F(1, 4) =	30.77	
Residual	509570014	4	127392504	Prob > F =	0.0052	
				R-squared	= 0.8849	
				Adj R-squared	= 0.8562	
Total	4.4290e+09	5	885800158	Root MSE =	11287	

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```

stark	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	14965.54	2698.068	5.55	0.005	7474.505	22456.58
_cons	688268.6	10507.47	65.50	0.000	659095.2	717442

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```

. reg summit year

```
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```

Source	SS	df	MS	Number of obs = 6		
Model	2.5354e+11	1	2.5354e+11	F(1, 4) =	49.21	
Residual	2.0610e+10	4	5.1524e+09	Prob > F =	0.0022	
				R-squared	= 0.9248	
				Adj R-squared	= 0.9060	
Total	2.7415e+11	5	5.4829e+10	Root MSE =	71780	

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```

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```

summit	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	120365.2	17158.78	7.01	0.002	72724.83	168005.6
_cons	1152755	66823.83	17.25	0.000	967222.5	1338288

```
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```

. reg trumbull year

```
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```

Source	SS	df	MS	Number of obs = 6		
Model	6.5611e+10	1	6.5611e+10	F(1, 4) =	68.63	
Residual	3.8243e+09	4	956069446	Prob > F =	0.0012	
				R-squared	= 0.9449	
				Adj R-squared	= 0.9312	
Total	6.9435e+10	5	1.3887e+10	Root MSE =	30920	

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```

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```

trumbull	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	61230.8	7391.383	8.28	0.001	40709.03	81752.57
_cons	1172514	28785.3	40.73	0.000	1092593	1252434

```
-----
```

. reg tuscarawas year

```
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```

Source	SS	df	MS	Number of obs = 6		
Model	4.5762e+09	1	4.5762e+09	F(1, 4) =	37.24	
Residual	491562849	4	122890712	Prob > F =	0.0036	
				R-squared	= 0.9030	
				Adj R-squared	= 0.8788	

```
-----
```

Total | 5.0677e+09 5 1.0135e+09 Root MSE = 11086

tuscarawas	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	16170.83	2649.967	6.10	0.004	8813.34	23528.32
_cons	357601.9	10320.14	34.65	0.000	328948.6	386255.2

. reg union year

Source	SS	df	MS	Number of obs = 6			
Model	2.2790e+09	1	2.2790e+09	F(1, 4) =	59.33	Prob > F =	0.0015
Residual	153641760	4	38410440	R-squared =	0.9368	Adj R-squared =	0.9211
Total	2.4326e+09	5	486523632	Root MSE =	6197.6		

union	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	11411.71	1481.514	7.70	0.002	7298.373	15525.06
_cons	238710.3	5769.666	41.37	0.000	222691.2	254729.5

. reg vanwert year

Source	SS	df	MS	Number of obs = 6			
Model	700775376	1	700775376	F(1, 4) =	45.98	Prob > F =	0.0025
Residual	60966151.3	4	15241537.8	R-squared =	0.9200	Adj R-squared =	0.9000
Total	761741527	5	152348305	Root MSE =	3904		

vanwert	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	6328.057	933.2444	6.78	0.002	3736.955	8919.159
_cons	140994.1	3634.465	38.79	0.000	130903.2	151085

. reg vinton year

Source	SS	df	MS	Number of obs = 6			
Model	400837072	1	400837072	F(1, 4) =	22.92	Prob > F =	0.0087
Residual	69954138.7	4	17488534.7	R-squared =	0.8514	Adj R-squared =	0.8143
Total	470791211	5	94158242.2	Root MSE =	4181.9		

vinton	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	4785.914	999.6724	4.79	0.009	2010.379	7561.45
_cons	84277.47	3893.165	21.65	0.000	73468.31	95086.62

. reg warren year

Source	SS	df	MS	Number of obs = 6			
Model	390158.229	1	390158.229	F(1, 4) =	0.00	Prob > F =	0.9748
Residual	1.3835e+09	4	345868125	R-squared =	0.0003		

```
-----+-----
Total | 1.3839e+09      5      276772532      Root MSE = 18598
Adj R-squared = -0.2496
```

```
-----+-----
warren | Coef.      Std. Err. t      P>|t|      [95% Conf. Interval]
-----+-----
year   | 149.3143    4445.66    0.03    0.975    -12193.82    12492.45
_cons  | 241470.4    17313.36   13.95   0.000    193400.8    289540
-----+-----
```

```
. reg washington year
```

```
Source | SS      df      MS      Number of obs = 6
-----+-----
Model  | 1.1516e+09    1    1.1516e+09    F( 1,      4) = 1.56
Residual | 2.9612e+09    4    740290427    Prob > F = 0.2804
Total   | 4.1127e+09    5    822543378    R-squared = 0.2800
Adj R-squared = 0.1000
Root MSE = 27208
```

```
-----+-----
washington | Coef.      Std. Err. t      P>|t|      [95% Conf. Interval]
-----+-----
year       | -8111.914    6504.023   -1.25   0.280    -26169.98    9946.147
_cons      | 577384.5     25329.53   22.79   0.000    507058.5    647710.6
-----+-----
```

```
. reg wayne year
```

```
Source | SS      df      MS      Number of obs = 6
-----+-----
Model  | 1.0147e+09    1    1.0147e+09    F( 1,      4) = 0.34
Residual | 1.2002e+10    4    3.0004e+09    Prob > F = 0.5921
Total   | 1.3016e+10    5    2.6033e+09    R-squared = 0.0780
Adj R-squared = -0.1526
Root MSE = 54776
```

```
-----+-----
wayne | Coef.      Std. Err. t      P>|t|      [95% Conf. Interval]
-----+-----
year   | 7614.771    13093.95    0.58   0.592    -28739.87    43969.41
_cons  | 775074.8     50993.62   15.20   0.000    633493.8    916655.8
-----+-----
```

```
. reg williams year
```

```
Source | SS      df      MS      Number of obs = 6
-----+-----
Model  | 2.8780e+09    1    2.8780e+09    F( 1,      4) = 32.86
Residual | 350358471     4    87589617.7    Prob > F = 0.0046
Total   | 3.2283e+09    5    645666675    R-squared = 0.8915
Adj R-squared = 0.8643
Root MSE = 9358.9
```

```
-----+-----
williams | Coef.      Std. Err. t      P>|t|      [95% Conf. Interval]
-----+-----
year     | 12824.03    2237.213    5.73   0.005    6612.53    19035.53
_cons    | 251525.1    8712.692    28.87   0.000    227334.8    275715.4
-----+-----
```

```
. reg wood year
```

```
Source | SS      df      MS      Number of obs = 6
-----+-----
Model  | 459966242     1    459966242    F( 1,      4) = 2.73
Prob > F = 0.1740
```

```

Residual |      674681157      4      168670289      R-squared      = 0.4054
-----+-----
Total | 1.1346e+09      5      226929480      Root MSE = 12987

```

```

-----+-----
wood | Coef.      Std. Err. t      P>|t|      [95% Conf. Interval]
-----+-----
year | 5126.771    3104.562    1.65    0.174    -3492.873    13746.42
_cons | 631290.8    12090.53    52.21   0.000    597722.1    664859.5

```

```
. reg wyandot year
```

```

Source | SS df MS      Number of obs = 6
-----+-----
Model | 853542577      1      853542577      F( 1,      4) = 22.66
Residual | 150667679      4      37666919.7      Prob > F = 0.0089
Total | 1.0042e+09      5      200842051      R-squared = 0.8500
                                           Adj R-squared = 0.8125
                                           Root MSE = 6137.3

```

```

-----+-----
wyandot | Coef.      Std. Err. t      P>|t|      [95% Conf. Interval]
-----+-----
year | 6983.829    1467.104    4.76    0.009    2910.494    11057.16
_cons | 115287.3    5713.551    20.18   0.000    99423.91    131150.6

```

County Time Trend Squared Estimates

```
. reg adams year year2
```

```

Source | SS df MS      Number of obs = 6
-----+-----
Model | 501151260      2      250575630      F( 2,      3) = 57.19
Residual | 13145107.3      3      4381702.42      Prob > F = 0.0041
Total | 514296367      5      102859273      R-squared = 0.9744
                                           Adj R-squared = 0.9574
                                           Root MSE = 2093.3

```

```

-----+-----
adams | Coef.      Std. Err. t      P>|t|      [95% Conf. Interval]
-----+-----
year | 6590.932    2449.769    2.69    0.074    -1205.326    14387.19
year2 | -177.9821    342.5887    -0.52   0.639    -1268.252    912.2881
_cons | 112490.3    3744.522    30.04   0.000    100573.6    124407

```

```
. reg allen year year2
```

```

Source | SS df MS      Number of obs = 6
-----+-----
Model | 2.5364e+09      2      1.2682e+09      F( 2,      3) = 4.87
Residual | 780575097      3      260191699      Prob > F = 0.1142
Total | 3.3170e+09      5      663400889      R-squared = 0.7647
                                           Adj R-squared = 0.6078
                                           Root MSE = 16130

```

```

-----+-----
allen | Coef.      Std. Err. t      P>|t|      [95% Conf. Interval]
-----+-----
year | -8952      18877.76    -0.47   0.668    -69029.45    51125.45
year2 | -438.5714    2639.966    -0.17   0.879    -8840.121    7962.979
_cons | 406172      28855.04    14.08   0.001    314342.4    498001.6

```

. reg ashland year year2

Source	SS	df	MS	Number of obs = 6			
Model	666133293	2	333066646	F(2, 3) =	3.10	Prob > F =	0.1862
Residual	322334869	3	107444956	R-squared =	0.6739	Adj R-squared =	0.4565
Total	988468162	5	197693632	Root MSE =	10366		

ashland	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	-4056.218	12131	-0.33	0.760	-42662.48	34550.05
year2	1410.268	1696.464	0.83	0.467	-3988.638	6809.173
_cons	315749.7	18542.49	17.03	0.000	256739.2	374760.2

. reg ashtabula year year2

Source	SS	df	MS	Number of obs = 6			
Model	1.6388e+09	2	819385407	F(2, 3) =	44.88	Prob > F =	0.0058
Residual	54777239.1	3	18259079.7	R-squared =	0.9677	Adj R-squared =	0.9461
Total	1.6935e+09	5	338709611	Root MSE =	4273.1		

ashtabula	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	-33817.72	5000.842	-6.76	0.007	-49732.64	-17902.81
year2	5577.304	699.3443	7.98	0.004	3351.678	7802.929
_cons	303892.1	7643.89	39.76	0.000	279565.8	328218.4

. reg athens year year2

Source	SS	df	MS	Number of obs = 6			
Model	6927254.16	2	3463627.08	F(2, 3) =	0.64	Prob > F =	0.5868
Residual	16233757.8	3	5411252.61	R-squared =	0.2991	Adj R-squared =	-0.1682
Total	23161012	5	4632202.4	Root MSE =	2326.2		

athens	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	-838.4679	2722.404	-0.31	0.778	-9502.372	7825.437
year2	199.4464	380.7155	0.52	0.637	-1012.16	1411.053
_cons	99395.7	4161.251	23.89	0.000	86152.74	112638.7

. reg auglaize year year2

Source	SS	df	MS	Number of obs = 6			
Model	364761370	2	182380685	F(2, 3) =	4.34	Prob > F =	0.1303
Residual	126148377	3	42049458.9	R-squared =	0.7430	Adj R-squared =	0.5717
Total	490909747	5	98181949.4	Root MSE =	6484.6		

auglaize	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	-838.4679	2722.404	-0.31	0.778	-9502.372	7825.437
year2	199.4464	380.7155	0.52	0.637	-1012.16	1411.053
_cons	99395.7	4161.251	23.89	0.000	86152.74	112638.7

	year	year2	_cons
	16831.51	-1884.089	212948.9
	7588.988	1061.285	11599.93
	2.22	-1.78	18.36
	0.113	0.174	0.000
	-7320.037	-5261.57	176032.8
	40983.06	1493.392	249865

. reg belmont year year2

Source	SS	df	MS	Number of obs = 6	F(2, 3) = 15.81
Model	5.8059e+09	2	2.9030e+09		Prob > F = 0.0255
Residual	550948848	3	183649616		R-squared = 0.9133
					Adj R-squared = 0.8556
Total	6.3569e+09	5	1.2714e+09		Root MSE = 13552

belmont	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
year	-21897.15	15859.84	-1.38	0.261	-72370.23 28575.92
year2	5466.875	2217.924	2.46	0.090	-1591.549 12525.3
_cons	354084.1	24242.09	14.61	0.001	276935 431233.2

. reg brown year year2

Source	SS	df	MS	Number of obs = 6	F(2, 3) = 1.85
Model	610170424	2	305085212		Prob > F = 0.2996
Residual	494727870	3	164909290		R-squared = 0.5522
					Adj R-squared = 0.2537
Total	1.1049e+09	5	220979659		Root MSE = 12842

brown	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
year	13936.71	15028.87	0.93	0.422	-33891.85 61765.28
year2	-1184.429	2101.717	-0.56	0.612	-7873.029 5504.172
_cons	139598	22971.93	6.08	0.009	66491.06 212704.9

. reg butler year year2

Source	SS	df	MS	Number of obs = 6	F(2, 3) = 1.73
Model	3.6787e+10	2	1.8393e+10		Prob > F = 0.3162
Residual	3.1862e+10	3	1.0621e+10		R-squared = 0.5359
					Adj R-squared = 0.2265
Total	6.8648e+10	5	1.3730e+10		Root MSE = 1.0e+05

butler	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
year	216917.6	120608.1	1.80	0.170	-166911.3 600746.5
year2	-28046.71	16866.48	-1.66	0.195	-81723.39 25629.97
_cons	646647.8	184352	3.51	0.039	59957.36 1233338

. reg carroll year year2

Source	SS	df	MS	Number of obs = 6	F(2, 3) = 4.29
Model	70016551	2	35008275.5		Prob > F = 0.1318
Residual	24464825.8	3	8154941.95		R-squared = 0.7411

```
-----+-----
Total | 94481376.8      5 18896275.4      Root MSE = 2855.7
Adj R-squared = 0.5684
```

```
-----+-----
      carroll | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
      year   | 6166.496  3342.059   1.85  0.162   -4469.427   16802.42
      year2  | -626.875  467.3713  -1.34  0.272   -2114.259   860.5091
      _cons  | 153619.7  5108.406  30.07  0.000   137362.5   169876.9
-----+-----
```

```
. reg champaign year year2
```

```
Source | SS   df MS   Number of obs = 6
-----+-----
Model | 283090570   2   141545285   F( 2, 3) = 15.41
Residual | 27552363.9   3   9184121.3   Prob > F = 0.0264
Total | 310642934   5   62128586.8   R-squared = 0.9113
Adj R-squared = 0.8522
Root MSE = 3030.5
```

```
-----+-----
      champaign | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
      year   | -3054.636  3546.684  -0.86  0.452   -14341.77   8232.495
      year2  | 973.8214  495.9871  1.96  0.144   -604.631   2552.274
      _cons  | 125947.6  5421.18  23.23  0.000   108695   143200.2
-----+-----
```

```
. reg clark year year2
```

```
Source | SS   df MS   Number of obs = 6
-----+-----
Model | 2.3624e+10   2   1.1812e+10   F( 2, 3) = 5.50
Residual | 6.4485e+09   3   2.1495e+09   Prob > F = 0.0993
Total | 3.0072e+10   5   6.0144e+09   R-squared = 0.7856
Adj R-squared = 0.6426
Root MSE = 46363
```

```
-----+-----
      clark | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
      year   | -64983.37  54259.05  -1.20  0.317   -237659.9   107693.1
      year2  | 4104.946  7587.874  0.54  0.626   -20043.06   28252.95
      _cons  | 447341.1  82936.08  5.39  0.012   183401.5   711280.7
-----+-----
```

```
. reg clermont year year2
```

```
Source | SS   df MS   Number of obs = 6
-----+-----
Model | 3.9969e+09   2   1.9985e+09   F( 2, 3) = 5.33
Residual | 1.1240e+09   3   374661362   Prob > F = 0.1028
Total | 5.1209e+09   5   1.0242e+09   R-squared = 0.7805
Adj R-squared = 0.6342
Root MSE = 19356
```

```
-----+-----
      clermont | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
      year   | 16316.91  22652.86  0.72  0.523   -55774.62   88408.43
      year2  | -172.3214  3167.897  -0.05  0.960   -10253.98   9909.341
      _cons  | 374209.2  34625.37  10.81  0.002   264015.8   484402.6
-----+-----
```

```
. reg clinton year year2
```

```

Source | SS df MS      Number of obs = 6
-----+-----
Model | 211215073      2    105607537      Prob > F = 0.0159
Residual | 14228310.1      3    4742770.02      R-squared = 0.9369
-----+-----
Total | 225443383      5    45088676.7      Adj R-squared = 0.8948
Root MSE = 2177.8

```

```

-----+-----
clinton | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
year | 15103.89   2548.706    5.93   0.010    6992.766   23215
year2 | -1844.286   356.4246   -5.17   0.014   -2978.588  -709.9836
_cons | 130884.4    3895.749   33.60   0.000   118486.4   143282.4
-----+-----

```

```
. reg columbiana year year2
```

```

Source | SS df MS      Number of obs = 6
-----+-----
Model | 5.4337e+09      2    2.7168e+09      Prob > F = 0.0458
Residual | 797179491      3    265726497      R-squared = 0.8721
-----+-----
Total | 6.2308e+09      5    1.2462e+09      Adj R-squared = 0.7868
Root MSE = 16301

```

```

-----+-----
columbiana | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
year | -55210.38   19077.48   -2.89   0.063   -115923.5   5502.687
year2 | 9451.589    2667.897    3.54   0.038    961.1506   17942.03
_cons | 665478.9    29160.33   22.82   0.000   572677.7   758280.1
-----+-----

```

```
. reg coshocton year year2
```

```

Source | SS df MS      Number of obs = 6
-----+-----
Model | 39173759.1      2    19586879.5      Prob > F = 0.8213
Residual | 279257810      3    93085936.8      R-squared = 0.1230
-----+-----
Total | 318431570      5    63686313.9      Adj R-squared = -0.4616
Root MSE = 9648.1

```

```

-----+-----
coshocton | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
year | 7123.461    11291.35    0.63   0.573   -28810.64   43057.56
year2 | -1023.911   1579.042   -0.65   0.563   -6049.127   4001.305
_cons | 157045.7    17259.06    9.10   0.003   102119.7   211971.7
-----+-----

```

```
. reg crawford year year2
```

```

Source | SS df MS      Number of obs = 6
-----+-----
Model | 64378060.4      2    32189030.2      Prob > F = 0.0997
Residual | 17639617.6      3    5879872.54      R-squared = 0.7849
-----+-----
Total | 82017678      5    16403535.6      Adj R-squared = 0.6415
Root MSE = 2424.8

```

```

-----+-----
crawford | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
year | 5964.279    2837.838    2.10   0.126   -3066.989   14995.55

```

year2	-609.3214	396.8584	-1.54	0.222	-1872.302	653.6591
_cons	90991.4	4337.694	20.98	0.000	77186.92	104795.9

. reg cuyahoga year year2

Source	SS	df	MS	Number of obs = 6		
Model	1.8274e+11	2	9.1372e+10	F(2, 3) =	62.41	
Residual	4.3920e+09	3	1.4640e+09	Prob > F =	0.0036	
Total	1.8714e+11	5	3.7427e+10	R-squared =	0.9765	
				Adj R-squared =	0.9609	
				Root MSE =	38262	

cuyahoga	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	140849.5	44778.74	3.15	0.051	-1656.418	283355.4
year2	-5569.321	6262.097	-0.89	0.439	-25498.11	14359.47
_cons	1031972	68445.23	15.08	0.001	814148.3	1249795

. reg darke year year2

Source	SS	df	MS	Number of obs = 6		
Model	3.9542e+09	2	1.9771e+09	F(2, 3) =	20.22	
Residual	293310580	3	97770193.4	Prob > F =	0.0181	
Total	4.2475e+09	5	849493320	R-squared =	0.9309	
				Adj R-squared =	0.8849	
				Root MSE =	9887.9	

darke	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	12672.69	11571.96	1.10	0.354	-24154.45	49499.83
year2	335.8571	1618.284	0.21	0.849	-4814.246	5485.96
_cons	496239.6	17687.98	28.06	0.000	439948.6	552530.6

. reg defiance year year2

Source	SS	df	MS	Number of obs = 6		
Model	2.7785e+10	2	1.3892e+10	F(2, 3) =	50.00	
Residual	833541771	3	277847257	Prob > F =	0.0050	
Total	2.8618e+10	5	5.7236e+09	R-squared =	0.9709	
				Adj R-squared =	0.9515	
				Root MSE =	16669	

defiance	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	-3317.104	19507.73	-0.17	0.876	-65399.41	58765.2
year2	6025.554	2728.065	2.21	0.114	-2656.366	14707.47
_cons	166620.3	29817.97	5.59	0.011	71726.22	261514.4

. reg delaware year year2

Source	SS	df	MS	Number of obs = 6		
Model	143760388	2	71880193.9	F(2, 3) =	6.73	
Residual	32041465.6	3	10680488.5	Prob > F =	0.0778	
Total	175801853	5	35160370.7	R-squared =	0.8177	
				Adj R-squared =	0.6962	
				Root MSE =	3268.1	

```
-----
```

delaware	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	4531.707	3824.716	1.18	0.321	-7640.247	16703.66
year2	-241.0357	534.8687	-0.45	0.683	-1943.227	1461.155
_cons	151450.4	5846.158	25.91	0.000	132845.3	170055.5

```
-----
```

. reg erie year year2

```
-----
```

Source	SS	df	MS	Number of obs = 6		
Model	1.0676e+09	2	533821635		F(2, 3) =	20.91
Residual	76575625.9	3	25525208.6		Prob > F =	0.0173
Total	1.1442e+09	5	228843779		R-squared =	0.9331
					Adj R-squared =	0.8885
					Root MSE =	5052.2

```
-----
```

```
-----
```

erie	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	8952.864	5912.734	1.51	0.227	-9864.093	27769.82
year2	-163.6786	826.8682	-0.20	0.856	-2795.142	2467.785
_cons	129014.6	9037.736	14.28	0.001	100252.5	157776.7

```
-----
```

. reg fairfield year year2

```
-----
```

Source	SS	df	MS	Number of obs = 6		
Model	536299695	2	268149847		F(2, 3) =	10.64
Residual	75631696.4	3	25210565.5		Prob > F =	0.0435
Total	611931391	5	122386278		R-squared =	0.8764
					Adj R-squared =	0.7940
					Root MSE =	5021

```
-----
```

```
-----
```

fairfield	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	8698.121	5876.178	1.48	0.235	-10002.5	27398.74
year2	-457.5357	821.756	-0.56	0.617	-3072.73	2157.659
_cons	166382.2	8981.86	18.52	0.000	137797.9	194966.5

```
-----
```

. reg fayette year year2

```
-----
```

Source	SS	df	MS	Number of obs = 6		
Model	101719040	2	50859520		F(2, 3) =	4.00
Residual	38130465.9	3	12710155.3		Prob > F =	0.1424
Total	139849506	5	27969901.2		R-squared =	0.7273
					Adj R-squared =	0.5456
					Root MSE =	3565.1

```
-----
```

```
-----
```

fayette	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	7082.486	4172.334	1.70	0.188	-6195.744	20360.72
year2	-699.8571	583.4814	-1.20	0.316	-2556.755	1157.041
_cons	127711.8	6377.499	20.03	0.000	107415.8	148007.8

```
-----
```

. reg franklin year year2

```
-----
```

Source	SS	df	MS	Number of obs = 6
--------	----	----	----	-------------------

```

-----+-----
Model | 3.2029e+11      2  1.6014e+11      Prob > F = 0.0122      F( 2,      3) = 26.88
Residual | 1.7876e+10      3  5.9585e+09      R-squared = 0.9471
-----+-----
Total | 3.3816e+11      5  6.7633e+10      Adj R-squared = 0.9119
Root MSE = 77192

```

```

-----+-----
franklin | Coef.      Std. Err. t      P>|t|      [95% Conf. Interval]
-----+-----
year | -141427.6    90338.66    -1.57    0.215    -428925.6    146070.3
year2 | 37843.75    12633.44     3.00    0.058    -2361.491    78048.99
_cons | 2337247     138084.5     16.93    0.000    1897801     2776694
-----+-----

```

```
. reg fulton year year2
```

```

Source | SS      df      MS      Number of obs = 6
-----+-----
Model | 791568928      2      395784464      Prob > F = 0.4641      F( 2,      3) = 1.00
Residual | 1.1846e+09      3      394874353      R-squared = 0.4006
-----+-----
Total | 1.9762e+09      5      395238397      Adj R-squared = 0.0009
Root MSE = 19871

```

```

-----+-----
fulton | Coef.      Std. Err. t      P>|t|      [95% Conf. Interval]
-----+-----
year | 11112.81     23255.9     0.48    0.665    -62897.84    85123.46
year2 | -635.9643    3252.229    -0.20    0.857    -10986.01    9714.079
_cons | 308533.8     35547.12    8.68    0.003    195407      421660.6
-----+-----

```

```
. reg gallia year year2
```

```

Source | SS      df      MS      Number of obs = 6
-----+-----
Model | 75272300.9      2      37636150.5      Prob > F = 0.4633      F( 2,      3) = 1.01
Residual | 112327159      3      37442386.4      R-squared = 0.4012
-----+-----
Total | 187599460      5      37519892      Adj R-squared = 0.0021
Root MSE = 6119

```

```

-----+-----
gallia | Coef.      Std. Err. t      P>|t|      [95% Conf. Interval]
-----+-----
year | 4643.7       7161.194    0.65    0.563    -18146.41    27433.81
year2 | -377.7857    1001.459    -0.38    0.731    -3564.877    2809.305
_cons | 198165.8     10946.03    18.10    0.000    163330.6    233001
-----+-----

```

```
. reg geauga year year2
```

```

Source | SS      df      MS      Number of obs = 6
-----+-----
Model | 4.5737e+10      2      2.2868e+10      Prob > F = 0.0596      F( 2,      3) = 8.33
Residual | 8.2350e+09      3      2.7450e+09      R-squared = 0.8474
-----+-----
Total | 5.3971e+10      5      1.0794e+10      Adj R-squared = 0.7457
Root MSE = 52393

```

```

-----+-----
geauga | Coef.      Std. Err. t      P>|t|      [95% Conf. Interval]
-----+-----
year | -108825.7    61316.02    -1.77    0.174    -303960.6    86309.26
year2 | 8459.839     8574.758     0.99    0.397    -18828.87    35748.55
_cons | 561011.3     93722.8     5.99    0.009    262743.5    859279.1
-----+-----

```

. reg greene year year2

```
Source | SS df MS Number of obs = 6
-----+-----
Model | 5.5060e+09 2 2.7530e+09 Prob > F = 0.1024
Residual | 1.5425e+09 3 514161630 R-squared = 0.7812
-----+-----
Total | 7.0485e+09 5 1.4097e+09 Root MSE = 22675
F( 2, 3) = 5.35
Adj R-squared = 0.6353
```

```
greene | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
year | 2903.375 26537.1 0.11 0.920 -81549.53 87356.28
year2 | -2876.625 3711.09 -0.78 0.495 -14686.97 8933.719
_cons | 229684.5 40562.51 5.66 0.011 100596.5 358772.5
```

. reg guernsey year year2

```
Source | SS df MS Number of obs = 6
-----+-----
Model | 1.2075e+09 2 603772114 Prob > F = 0.0052
Residual | 37208185.9 3 12402728.6 R-squared = 0.9701
-----+-----
Total | 1.2448e+09 5 248950483 Root MSE = 3521.8
Adj R-squared = 0.9502
```

```
guernsey | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
year | -2416.014 4121.566 -0.59 0.599 -15532.68 10700.65
year2 | 1490.357 576.3818 2.59 0.081 -343.9469 3324.661
_cons | 148991.8 6299.899 23.65 0.000 128942.7 169040.9
```

. reg hamilton year year2

```
Source | SS df MS Number of obs = 6
-----+-----
Model | 1.3077e+11 2 6.5383e+10 Prob > F = 0.0202
Residual | 1.0462e+10 3 3.4875e+09 R-squared = 0.9259
-----+-----
Total | 1.4123e+11 5 2.8246e+10 Root MSE = 59055
Adj R-squared = 0.8765
```

```
hamilton | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
year | 124751.8 69112.72 1.81 0.169 -95195.72 344699.3
year2 | -5526.661 9665.091 -0.57 0.607 -36285.29 25231.97
_cons | 1488585 105640.2 14.09 0.001 1152391 1824779
```

. reg hancock year year2

```
Source | SS df MS Number of obs = 6
-----+-----
Model | 697852143 2 348926071 Prob > F = 0.2818
Residual | 526181975 3 175393992 R-squared = 0.5701
-----+-----
Total | 1.2240e+09 5 244806823 Root MSE = 13244
Adj R-squared = 0.2835
```

	hancock	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year		26049.05	15499.26	1.68	0.191	-23276.52	75374.62
year2		-3090.411	2167.499	-1.43	0.249	-9988.361	3807.54
_cons		284267.9	23690.94	12.00	0.001	208872.7	359663.1

. reg hardin year year2

Source	SS	df	MS	Number of obs = 6			
Model		487960115	2	243980057	F(2, 3) =	52.87	
Residual		13843852.9	3	4614617.62	Prob > F =	0.0046	
Total		501803968	5	100360794	R-squared =	0.9724	
					Adj R-squared =	0.9540	
					Root MSE =	2148.2	

	hardin	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year		3778.786	2514.036	1.50	0.230	-4222	11779.57
year2		213.2143	351.5762	0.61	0.587	-905.6581	1332.087
_cons		155499	3842.756	40.47	0.000	143269.6	167728.4

. reg harrison year year2

Source	SS	df	MS	Number of obs = 6			
Model		290450740	2	145225370	F(2, 3) =	11.33	
Residual		38465361.7	3	12821787.2	Prob > F =	0.0400	
Total		328916102	5	65783220.3	R-squared =	0.8831	
					Adj R-squared =	0.8051	
					Root MSE =	3580.8	

	harrison	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year		7763.582	4190.617	1.85	0.161	-5572.831	21100
year2		-538.0179	586.0382	-0.92	0.426	-2403.053	1327.017
_cons		89081.9	6405.444	13.91	0.001	68696.92	109466.9

. reg henry year year2

Source	SS	df	MS	Number of obs = 6			
Model		520806263	2	260403131	F(2, 3) =	7.26	
Residual		107648475	3	35882824.9	Prob > F =	0.0709	
Total		628454737	5	125690947	R-squared =	0.8287	
					Adj R-squared =	0.7145	
					Root MSE =	5990.2	

	henry	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year		23849.88	7010.468	3.40	0.042	1539.442	46160.32
year2		-2921.607	980.3811	-2.98	0.059	-6041.617	198.4031
_cons		276576.8	10715.64	25.81	0.000	242474.8	310678.8

. reg highland year year2

Source	SS	df	MS	Number of obs = 6			
Model		490578510	2	245289255	F(2, 3) =	58.69	
					Prob > F =	0.0039	

```

Residual | 12537787.8      3  4179262.61      R-squared    = 0.9751
-----+-----
Total    | 503116298      5  100623260      Root MSE = 2044.3

```

```

-----+-----
highland | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
year     | 5556.468 2392.509   2.32  0.103   -2057.562   13170.5
year2    | -37.44643 334.5811  -0.11  0.918   -1102.233   1027.34
_cons    | 137270.3  3656.999  37.54  0.000   125632.1   148908.5

```

. reg hocking year year2

```

Source | SS   df MS   Number of obs = 6
-----+-----
Model  | 115603173   2  57801586.4   Prob > F = 0.2245
Residual | 67720120.5   3  22573373.5   R-squared = 0.6306
-----+-----
Total  | 183323293   5  36664658.7   Adj R-squared = 0.3843
Root MSE = 4751.1

```

```

-----+-----
hocking | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
year     | 7933.761 5560.347   1.43  0.249   -9761.745   25629.27
year2    | -807.125  777.5885  -1.04  0.376   -3281.759   1667.509
_cons    | 83212.9  8499.106   9.79  0.002   56164.95   110260.8

```

. reg holmes year year2

```

Source | SS   df MS   Number of obs = 6
-----+-----
Model  | 4.9232e+09   2  2.4616e+09   Prob > F = 0.0130
Residual | 288351001   3  96117000.4   R-squared = 0.9447
-----+-----
Total  | 5.2116e+09   5  1.0423e+09   Adj R-squared = 0.9078
Root MSE = 9803.9

```

```

-----+-----
holmes  | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
year     | 22091.2  11473.71   1.93  0.150   -14423.26   58605.65
year2    | -765.0893 1604.544  -0.48  0.666   -5871.465   4341.287
_cons    | 249278.5  17537.8   14.21  0.001   193465.4   305091.6

```

. reg huron year year2

```

Source | SS   df MS   Number of obs = 6
-----+-----
Model  | 293214151   2  146607075   Prob > F = 0.1422
Residual | 109821840   3  36607280.1   R-squared = 0.7275
-----+-----
Total  | 403035991   5  80607198.3   Adj R-squared = 0.5459
Root MSE = 6050.4

```

```

-----+-----
huron   | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
year     | 18208  7080.883   2.57  0.082   -4326.533   40742.53
year2    | -2253.518 990.2283  -2.28  0.107   -5404.866   897.8306
_cons    | 262696.7 10823.28  24.27  0.000   228252.2   297141.2

```

. reg jackson year year2

Source	SS	df	MS	Number of obs = 6		
Model	254300366	2	127150183			F(2, 3) = 3.56
Residual	107097699	3	35699233			Prob > F = 0.1613
						R-squared = 0.7037
						Adj R-squared = 0.5061
Total	361398065	5	72279613			Root MSE = 5974.9

jackson	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	15457.66	6992.51	2.21	0.114	-6795.624	37710.95
year2	-1817.393	977.8699	-1.86	0.160	-4929.411	1294.625
_cons	142844.8	10688.2	13.36	0.001	108830.2	176859.4

. reg jefferson year year2

Source	SS	df	MS	Number of obs = 6		
Model	6.4194e+09	2	3.2097e+09			F(2, 3) = 38.41
Residual	250674127	3	83558042.4			Prob > F = 0.0073
						R-squared = 0.9624
						Adj R-squared = 0.9374
Total	6.6701e+09	5	1.3340e+09			Root MSE = 9141

jefferson	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	-14615.96	10697.88	-1.37	0.265	-48661.4	19429.47
year2	4646.554	1496.049	3.11	0.053	-114.5412	9407.648
_cons	188450.3	16351.93	11.52	0.001	136411.1	240489.5

. reg knox year year2

Source	SS	df	MS	Number of obs = 6		
Model	759252050	2	379626025			F(2, 3) = 241.14
Residual	4722825.51	3	1574275.17			Prob > F = 0.0005
						R-squared = 0.9938
						Adj R-squared = 0.9897
Total	763974876	5	152794975			Root MSE = 1254.7

knox	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	7338.664	1468.399	5.00	0.015	2665.564	12011.76
year2	-107.6786	205.3487	-0.52	0.636	-761.1898	545.8326
_cons	181829.8	2244.478	81.01	0.000	174686.9	188972.7

. reg lake year year2

Source	SS	df	MS	Number of obs = 6		
Model	7244381.92	2	3622190.96			F(2, 3) = 0.58
Residual	18856448.9	3	6285482.97			Prob > F = 0.6141
						R-squared = 0.2776
						Adj R-squared = -0.2041
Total	26100830.8	5	5220166.17			Root MSE = 2507.1

lake	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
------	-------	-----------	---	------	----------------------	--

year		2537.043	2934.087	0.86	0.451	-6800.532	11874.62
year2		-400.6429	410.3184	-0.98	0.401	-1706.459	905.1733
_cons		144285.6	4484.813	32.17	0.000	130012.9	158558.3

. reg lawrence year year2

Source		SS	df	MS	Number of obs = 6		
Model		729486103	2	364743052		F(2, 3) =	12.11
Residual		90364001.9	3	30121334		Prob > F =	0.0366
Total		819850105	5	163970021		R-squared =	0.8898
						Adj R-squared =	0.8163
						Root MSE =	5488.3

lawrence		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year		-23198.99	6423.042	-3.61	0.036	-43639.98	-2758.006
year2		2562.607	898.2324	2.85	0.065	-295.9692	5421.184
_cons		267722.6	9817.753	27.27	0.000	236478.1	298967.1

. reg licking year year2

Source		SS	df	MS	Number of obs = 6		
Model		257531375	2	128765687		F(2, 3) =	2.89
Residual		133866092	3	44622030.8		Prob > F =	0.2000
Total		391397467	5	78279493.5		R-squared =	0.6580
						Adj R-squared =	0.4300
						Root MSE =	6680

licking		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year		400.7679	7817.688	0.05	0.962	-24478.6	25280.14
year2		481.4821	1093.267	0.44	0.689	-2997.782	3960.746
_cons		308890.5	11949.5	25.85	0.000	270861.9	346919.1

. reg logan year year2

Source		SS	df	MS	Number of obs = 6		
Model		2.8995e+09	2	1.4498e+09		F(2, 3) =	13.93
Residual		312191856	3	104063952		Prob > F =	0.0303
Total		3.2117e+09	5	642341977		R-squared =	0.9028
						Adj R-squared =	0.8380
						Root MSE =	10201

logan		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year		-20614.77	11938.61	-1.73	0.183	-58608.76	17379.22
year2		4523.143	1669.559	2.71	0.073	-790.139	9836.425
_cons		148356.2	18248.41	8.13	0.004	90281.6	206430.8

. reg lorain year year2

Source		SS	df	MS	Number of obs = 6		
Model		3.5307e+09	2	1.7653e+09		F(2, 3) =	37.68
Residual		140542356	3	46847451.9		Prob > F =	0.0075
Total		3.6712e+09	5	734247971.8		R-squared =	0.9617
						Adj R-squared =	0.9362

Total | 3.6712e+09 5 734241590 Root MSE = 6844.5

lorain	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	13437.93	8010.261	1.68	0.192	-12054.29	38930.16
year2	109.3036	1120.198	0.10	0.928	-3455.665	3674.272
_cons	241185.3	12243.85	19.70	0.000	202219.9	280150.7

. reg lucas year year2

Source	SS	df	MS	Number of obs = 6		
Model	8.4428e+09	2	4.2214e+09	F(2, 3) =	14.57	
Residual	869398981	3	289799660	Prob > F =	0.0285	
Total	9.3122e+09	5	1.8624e+09	R-squared =	0.9066	
				Adj R-squared =	0.8444	
				Root MSE =	17024	

lucas	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	6741.071	19922.9	0.34	0.757	-56662.5	70144.64
year2	2142.786	2786.125	0.77	0.498	-6723.907	11009.48
_cons	754220	30452.57	24.77	0.000	657306.3	851133.7

. reg madison year year2

Source	SS	df	MS	Number of obs = 6		
Model	2.8077e+09	2	1.4038e+09	F(2, 3) =	23.38	
Residual	180119725	3	60039908.4	Prob > F =	0.0148	
Total	2.9878e+09	5	597557465	R-squared =	0.9397	
				Adj R-squared =	0.8995	
				Root MSE =	7748.5	

madison	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	12172.75	9068.254	1.34	0.272	-16686.48	41031.98
year2	70.46429	1268.153	0.06	0.959	-3965.364	4106.293
_cons	175511	13861.01	12.66	0.001	131399.1	219622.9

. reg mahoning year year2

Source	SS	df	MS	Number of obs = 6		
Model	3.9676e+11	2	1.9838e+11	F(2, 3) =	8.48	
Residual	7.0180e+10	3	2.3393e+10	Prob > F =	0.0583	
Total	4.6694e+11	5	9.3389e+10	R-squared =	0.8497	
				Adj R-squared =	0.7495	
				Root MSE =	1.5e+05	

mahoning	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	389584.8	178998.5	2.18	0.118	-180068.3	959238
year2	-35456.89	25032.1	-1.42	0.252	-115120.2	44206.43
_cons	732906.4	273602.9	2.68	0.075	-137820.2	1603633

. reg marion year year2

```

Source | SS df MS      Number of obs = 6
-----+-----
Model | 477726269      2    238863135      F( 2, 3) = 14.86
Residual | 48209306.1      3    16069768.7      Prob > F = 0.0278
-----+-----
Total | 525935575      5    105187115      R-squared = 0.9083
                          Adj R-squared = 0.8472
                          Root MSE = 4008.7

```

```

marion | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
year   | 6840.646  4691.465    1.46  0.241   -8089.689   21770.98
year2  | -232.4107  656.0794   -0.35  0.747   -2320.348   1855.527
_cons  | 127151.3   7171.001   17.73  0.000   104330     149972.6

```

```
. reg medina year year2
```

```

Source | SS df MS      Number of obs = 6
-----+-----
Model | 1.0150e+10      2  5.0751e+09      F( 2, 3) = 47.29
Residual | 321975057      3  107325019      Prob > F = 0.0054
-----+-----
Total | 1.0472e+10      5  2.0944e+09      R-squared = 0.9693
                          Adj R-squared = 0.9488
                          Root MSE = 10360

```

```

medina | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
year   | 27717.12  12124.23    2.29  0.106   -10867.59   66301.83
year2  | -520.8214  1695.517   -0.31  0.779   -5916.713   4875.07
_cons  | 326023.2  18532.14   17.59  0.000   267045.7   385000.7

```

```
. reg meigs year year2
```

```

Source | SS df MS      Number of obs = 6
-----+-----
Model | 150286383      2  75143191.5      F( 2, 3) = 9.05
Residual | 24912902.3      3  8304300.78      Prob > F = 0.0536
-----+-----
Total | 175199285      5  35039857.1      R-squared = 0.8578
                          Adj R-squared = 0.7630
                          Root MSE = 2881.7

```

```

meigs | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
year   | 680.8857  3372.525    0.20  0.853   -10051.99   11413.77
year2  | 316.1429  471.6319    0.67  0.551   -1184.8     1817.086
_cons  | 102237.4  5154.975   19.83  0.000   85831.97   118642.8

```

```
. reg mercer year year2
```

```

Source | SS df MS      Number of obs = 6
-----+-----
Model | 2.5465e+10      2  1.2733e+10      F( 2, 3) = 13.60
Residual | 2.8092e+09      3  936395808      Prob > F = 0.0313
-----+-----
Total | 2.8275e+10      5  5.6549e+09      R-squared = 0.9006
                          Adj R-squared = 0.8344
                          Root MSE = 30601

```

```

mercer | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
year   | 60475.49  35812.4    1.69  0.190   -53495.55   174446.5
year2  | -3231.714  5008.196   -0.65  0.565   -19170.03   12706.6

```

```

_cons | 392015.8 54739.99 7.16 0.006 217808.7 566222.9
-----

```

```
. reg miami year year2
```

```

Source | SS df MS Number of obs = 6
-----+-----
Model | 2.9617e+09 2 1.4809e+09 Prob > F = 0.0439
Residual | 420675846 3 140225282 R-squared = 0.8756
-----+-----
Total | 3.3824e+09 5 676475423 Root MSE = 11842
Adj R-squared = 0.7927
F( 2, 3) = 10.56

```

```

-----
miami | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
year | 21049.79 13858.52 1.52 0.226 -23054.2 65153.79
year2 | -1164.607 1938.049 -0.60 0.590 -7332.344 5003.13
_cons | 263876.6 21183.03 12.46 0.001 196462.7 331290.5
-----

```

```
. reg monroe year year2
```

```

Source | SS df MS Number of obs = 6
-----+-----
Model | 288816548 2 144408274 Prob > F = 0.0949
Residual | 75894250.9 3 25298083.6 R-squared = 0.7919
-----+-----
Total | 364710799 5 72942159.9 Root MSE = 5029.7
Adj R-squared = 0.6532
F( 2, 3) = 5.71

```

```

-----
monroe | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
year | 7720.836 5886.369 1.31 0.281 -11012.22 26453.89
year2 | -533.3929 823.1812 -0.65 0.563 -3153.123 2086.337
_cons | 106713.2 8997.437 11.86 0.001 78079.34 135347.1
-----

```

```
. reg montgomery year year2
```

```

Source | SS df MS Number of obs = 6
-----+-----
Model | 3.2212e+10 2 1.6106e+10 Prob > F = 0.0077
Residual | 1.3025e+09 3 434163345 R-squared = 0.9611
-----+-----
Total | 3.3515e+10 5 6.7030e+09 Root MSE = 20837
Adj R-squared = 0.9352
F( 2, 3) = 37.10

```

```

-----
montgomery | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
year | -6073.029 24385.42 -0.25 0.819 -83678.32 71532.26
year2 | 6828.714 3410.187 2.00 0.139 -4024.023 17681.45
_cons | 787318.6 37273.62 21.12 0.000 668697.3 905939.9
-----

```

```
. reg morgan year year2
```

```

Source | SS df MS Number of obs = 6
-----+-----
Model | 203690079 2 101845039 Prob > F = 0.0044
Residual | 5626608.34 3 1875536.11 R-squared = 0.9731
-----+-----
Total | 209316687 5 41863337.5 Root MSE = 1369.5
Adj R-squared = 0.9552
F( 2, 3) = 54.30

```

```
-----
```

morgan	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	3019.686	1602.752	1.88	0.156	-2080.987	8120.359
year2	55.85714	224.1374	0.25	0.819	-657.4481	769.1624
_cons	78379.6	2449.84	31.99	0.000	70583.12	86176.08

```
-----
```

. reg morrow year year2

```
-----
```

Source	SS	df	MS	Number of obs = 6		
Model	127642315	2	63821157.7	F(2, 3) =	5.89	
Residual	32515779.4	3	10838593.1	Prob > F =	0.0915	
Total	160158095	5	32031619	R-squared =	0.7970	
				Adj R-squared =	0.6616	
				Root MSE =	3292.2	

```
-----
```

```
-----
```

morrow	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	9687.582	3852.921	2.51	0.087	-2574.133	21949.3
year2	-1069.161	538.813	-1.98	0.141	-2783.904	645.5828
_cons	113693.9	5889.27	19.31	0.000	94951.62	132436.2

```
-----
```

. reg muskingum year year2

```
-----
```

Source	SS	df	MS	Number of obs = 6		
Model	1.7253e+09	2	862625488	F(2, 3) =	7.36	
Residual	351537205	3	117179068	Prob > F =	0.0696	
Total	2.0768e+09	5	415357636	R-squared =	0.8307	
				Adj R-squared =	0.7179	
				Root MSE =	10825	

```
-----
```

```
-----
```

muskingum	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	-18898.22	12668.6	-1.49	0.233	-59215.36	21418.93
year2	3866.411	1771.645	2.18	0.117	-1771.754	9504.575
_cons	280362.7	19364.22	14.48	0.001	218737.1	341988.3

```
-----
```

. reg noble year year2

```
-----
```

Source	SS	df	MS	Number of obs = 6		
Model	780109836	2	390054918	F(2, 3) =	91.72	
Residual	12757589.1	3	4252529.7	Prob > F =	0.0020	
Total	792867426	5	158573485	R-squared =	0.9839	
				Adj R-squared =	0.9732	
				Root MSE =	2062.2	

```
-----
```

```
-----
```

noble	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	-860.1321	2413.389	-0.36	0.745	-8540.613	6820.349
year2	1051.125	337.5012	3.11	0.053	-22.95438	2125.204
_cons	112823.9	3688.915	30.58	0.000	101084.1	124563.7

```
-----
```

. reg ottawa year year2

```
-----
```

Source	SS	df	MS	Number of obs = 6		
Model				F(2, 3) =	5.36	

```
-----
```

```

Model | 185528509 2 92764254.7 Prob > F = 0.1023
Residual | 51933405.4 3 17311135.1 R-squared = 0.7813
-----+-----
Total | 237461915 5 47492383 Root MSE = 4160.7
Adj R-squared = 0.6355

```

```

-----+-----
ottawa | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
year | 4435.918 4869.299 0.91 0.429 -11060.36 19932.2
year2 | -169.9107 680.9487 -0.25 0.819 -2336.993 1997.172
_cons | 128845.1 7442.824 17.31 0.000 105158.7 152531.5
-----+-----

```

. reg paulding year year2

```

Source | SS df MS Number of obs = 6
-----+-----
Model | 955781477 2 477890738 F( 2, 3) = 7.88
Residual | 181880273 3 60626757.8 Prob > F = 0.0639
Total | 1.1377e+09 5 227532350 R-squared = 0.8401
Adj R-squared = 0.7335
Root MSE = 7786.3

```

```

-----+-----
paulding | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
year | 25252.96 9112.464 2.77 0.069 -3746.971 54252.89
year2 | -2716.929 1274.336 -2.13 0.123 -6772.433 1338.576
_cons | 96914.4 13928.59 6.96 0.006 52587.41 141241.4
-----+-----

```

. reg perry year year2

```

Source | SS df MS Number of obs = 6
-----+-----
Model | 18141449.3 2 9070724.66 F( 2, 3) = 13.37
Residual | 2035765.51 3 678588.505 Prob > F = 0.0320
Total | 20177214.8 5 4035442.97 R-squared = 0.8991
Adj R-squared = 0.8318
Root MSE = 823.76

```

```

-----+-----
perry | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
year | -1321.336 964.0663 -1.37 0.264 -4389.425 1746.754
year2 | 318.1786 134.8202 2.36 0.099 -110.8794 747.2365
_cons | 105654.8 1473.595 71.70 0.000 100965.2 110344.4
-----+-----

```

. reg pickaway year year2

```

Source | SS df MS Number of obs = 6
-----+-----
Model | 33018244.8 2 16509122.4 F( 2, 3) = 2.11
Residual | 23451562.5 3 7817187.51 Prob > F = 0.2676
Total | 56469807.3 5 11293961.5 R-squared = 0.5847
Adj R-squared = 0.3078
Root MSE = 2795.9

```

```

-----+-----
pickaway | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
year | 6330.046 3272.118 1.93 0.149 -4083.293 16743.39
year2 | -931.4107 457.5904 -2.04 0.135 -2387.668 524.8461
_cons | 116972.9 5001.5 23.39 0.000 101055.9 132889.9
-----+-----

```

. reg pike year year2

Source	SS	df	MS	Number of obs = 6			
Model	884139592	2	442069796	442069796	2	F(2, 3) =	34.37
Residual	38587643.1	3	12862547.7	12862547.7	3	Prob > F =	0.0086
						R-squared	= 0.9582
						Adj R-squared	= 0.9303
Total	922727235	5	184545447	184545447	5	Root MSE =	3586.4

pike	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	9417.189	4197.273	2.24	0.111	-3940.405	22774.78
year2	-332.2679	586.9689	-0.57	0.611	-2200.265	1535.729
_cons	123795.9	6415.618	19.30	0.000	103378.5	144213.3

. reg portage year year2

Source	SS	df	MS	Number of obs = 6			
Model	1.1866e+10	2	5.9332e+09	5.9332e+09	2	F(2, 3) =	27.79
Residual	640558009	3	213519336	213519336	3	Prob > F =	0.0116
						R-squared	= 0.9488
						Adj R-squared	= 0.9146
Total	1.2507e+10	5	2.5014e+09	2.5014e+09	5	Root MSE =	14612

portage	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	24311.26	17101.03	1.42	0.250	-30111.85	78734.37
year2	246.6071	2391.499	0.10	0.924	-7364.21	7857.425
_cons	467077.2	26139.28	17.87	0.000	383890.3	550264.1

. reg preble year year2

Source	SS	df	MS	Number of obs = 6			
Model	152273631	2	76136815.4	76136815.4	2	F(2, 3) =	0.90
Residual	254503248	3	84834416	84834416	3	Prob > F =	0.4949
						R-squared	= 0.3743
						Adj R-squared	= -0.0428
Total	406776879	5	81355375.8	81355375.8	5	Root MSE =	9210.6

preble	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	2923.425	10779.28	0.27	0.804	-31381.05	37227.9
year2	3.767857	1507.432	0.00	0.998	-4793.553	4801.088
_cons	256667.7	16476.35	15.58	0.001	204232.6	309102.8

. reg putnam year year2

Source	SS	df	MS	Number of obs = 6			
Model	388969801	2	194484900	194484900	2	F(2, 3) =	2.29
Residual	254525398	3	84841799.3	84841799.3	3	Prob > F =	0.2488
						R-squared	= 0.6045
						Adj R-squared	= 0.3408
Total	643495199	5	128699040	128699040	5	Root MSE =	9211

putnam	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	2923.425	10779.28	0.27	0.804	-31381.05	37227.9
year2	3.767857	1507.432	0.00	0.998	-4793.553	4801.088
_cons	256667.7	16476.35	15.58	0.001	204232.6	309102.8

	year	year2	_cons
	8092.8	-490.4286	194764.2
	10779.75	1507.497	16477.07
	0.75	-0.33	11.82
	0.507	0.766	0.001
	-26213.17	-5287.958	142326.8
	42398.77	4307.101	247201.6

. reg richland year year2

Source	SS	df	MS	Number of obs = 6	F(2, 3) = 1.54
Model	44586364.5	2	22293182.3		Prob > F = 0.3465
Residual	43406262.8	3	14468754.3		R-squared = 0.5067
Total	87992627.3	5	17598525.5		Adj R-squared = 0.1778
					Root MSE = 3803.8

richland	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
year	7350.654	4451.632	1.65	0.197	-6816.426 21517.73
year2	-930.5179	622.5399	-1.49	0.232	-2911.718 1050.682
_cons	187909.9	6804.411	27.62	0.000	166255.2 209564.6

. reg ross year year2

Source	SS	df	MS	Number of obs = 6	F(2, 3) = 5.64
Model	456342840	2	228171420		Prob > F = 0.0964
Residual	121467771	3	40489257.2		R-squared = 0.7898
Total	577810612	5	115562122		Adj R-squared = 0.6496
					Root MSE = 6363.1

ross	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
year	-4496.757	7446.867	-0.60	0.589	-28196.01 19202.5
year2	1318.071	1041.409	1.27	0.295	-1996.158 4632.301
_cons	185398.4	11382.69	16.29	0.001	149173.6 221623.2

. reg sandusky year year2

Source	SS	df	MS	Number of obs = 6	F(2, 3) = 1.59
Model	166379506	2	83189752.8		Prob > F = 0.3383
Residual	156984460	3	52328153.3		R-squared = 0.5145
Total	323363965	5	64672793.1		Adj R-squared = 0.1909
					Root MSE = 7233.8

sandusky	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
year	8043.329	8465.866	0.95	0.412	-18898.83 34985.49
year2	-736.2143	1183.912	-0.62	0.578	-4503.95 3031.521
_cons	197083.6	12940.25	15.23	0.001	155901.9 238265.3

. reg scioto year year2

Source	SS	df	MS	Number of obs = 6	F(2, 3) = 2.00
Model	59668084.6	2	29834042.3		Prob > F = 0.2803
Residual	44703968.9	3	14901323		R-squared = 0.5717
Total					Adj R-squared = 0.2861

Total | 104372054 5 20874410.7 Root MSE = 3860.2

scioto	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	6831.386	4517.686	1.51	0.228	-7545.909	21208.68
year2	-766.0714	631.7773	-1.21	0.312	-2776.669	1244.526
_cons	258305.4	6905.377	37.41	0.000	236329.4	280281.4

. reg seneca year year2

Source	SS	df	MS	Number of obs = 6	F(2, 3) = 1.59
Model	87737384.3	2	43868692.1	Prob > F = 0.3389	
Residual	82986007.7	3	27662002.6	R-squared = 0.5139	
Total	170723392	5	34144678.4	Adj R-squared = 0.1899	Root MSE = 5259.5

seneca	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	10649.86	6155.247	1.73	0.182	-8938.886	30238.6
year2	-1532.143	860.7825	-1.78	0.173	-4271.537	1207.251
_cons	213442	9408.422	22.69	0.000	183500.2	243383.8

. reg shelby year year2

Source	SS	df	MS	Number of obs = 6	F(2, 3) = 4.48
Model	1.7704e+09	2	885200111	Prob > F = 0.1256	
Residual	592460837	3	197486946	R-squared = 0.7493	
Total	2.3629e+09	5	472572212	Adj R-squared = 0.5821	Root MSE = 14053

shelby	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	-23933.87	16446.48	-1.46	0.242	-76273.9	28406.16
year2	2047.214	2299.963	0.89	0.439	-5272.294	9366.722
_cons	588282.8	25138.78	23.40	0.000	508280	668285.6

. reg stark year year2

Source	SS	df	MS	Number of obs = 6	F(2, 3) = 12.20
Model	3.9440e+09	2	1.9720e+09	Prob > F = 0.0362	
Residual	485017260	3	161672420	R-squared = 0.8905	
Total	4.4290e+09	5	885800158	Adj R-squared = 0.8175	Root MSE = 12715

stark	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	9288.793	14880.64	0.62	0.577	-38068.05	56645.63
year2	810.9643	2080.988	0.39	0.723	-5811.668	7433.597
_cons	695837.6	22745.37	30.59	0.000	623451.7	768223.5

. reg summit year year2

```

Source | SS df MS      Number of obs = 6
-----+-----
Model | 2.5439e+11  2  1.2720e+11   F( 2, 3) = 19.32
Residual | 1.9752e+10  3  6.5839e+09   Prob > F = 0.0193
Total | 2.7415e+11  5  5.4829e+10   R-squared = 0.9280
                                           Adj R-squared = 0.8799
                                           Root MSE = 81141

```

```

summit | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
year   | 153924.4  94960.72   1.62  0.203   -148283   456131.7
year2  | -4794.161 13279.81  -0.36  0.742   -47056.45  37468.13
_cons  | 1108010  145149.4   7.63  0.005   646079.4  1569940

```

```
. reg trumbull year year2
```

```

Source | SS df MS      Number of obs = 6
-----+-----
Model | 6.6016e+10  2  3.3008e+10   F( 2, 3) = 28.96
Residual | 3.4193e+09  3  1.1398e+09   Prob > F = 0.0109
Total | 6.9435e+10  5  1.3887e+10   R-squared = 0.9508
                                           Adj R-squared = 0.9179
                                           Root MSE = 33760

```

```

trumbull | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
year   | 84286.42  39510.29   2.13  0.123   -41452.97  210025.8
year2  | -3293.661  5525.33  -0.60  0.593   -20877.73  14290.4
_cons  | 1141773  60392.3   18.91  0.000   949577.4  1333968

```

```
. reg tuscarawas year year2
```

```

Source | SS df MS      Number of obs = 6
-----+-----
Model | 4.9801e+09  2  2.4901e+09   F( 2, 3) = 85.27
Residual | 87607862.5  3  29202620.8   Prob > F = 0.0023
Total | 5.0677e+09  5  1.0135e+09   R-squared = 0.9827
                                           Adj R-squared = 0.9712
                                           Root MSE = 5403.9

```

```

tuscarawas | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
year   | -6855.046  6324.331  -1.08  0.358   -26981.89  13271.8
year2  | 3289.411  884.4281  3.72  0.034   474.7658  6104.056
_cons  | 388303.1  9666.871  40.17  0.000   357538.8  419067.4

```

```
. reg union year year2
```

```

Source | SS df MS      Number of obs = 6
-----+-----
Model | 2.3269e+09  2  1.1634e+09   F( 2, 3) = 33.00
Residual | 105753620  3  35251206.6   Prob > F = 0.0091
Total | 2.4326e+09  5  486523632   R-squared = 0.9565
                                           Adj R-squared = 0.9275
                                           Root MSE = 5937.3

```

```

union | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
year   | 3483.714  6948.494   0.50  0.651   -18629.49  25596.92
year2  | 1132.571  971.7143  1.17  0.328   -1959.857  4225

```

```
_cons |      249281   10620.92   23.47   0.000   215480.5   283081.5
```

```
. reg vanwert year year2
```

```
Source |  SS  df  MS      Number of obs = 6
-----+-----
Model |  728774888    2   364387444    F( 2,    3) = 33.16
Residual | 32966639.3    3  10988879.8    Prob > F = 0.0090
-----+-----
Total |  761741527    5  152348305    R-squared   = 0.9567
                                           Adj R-squared = 0.9279
                                           Root MSE = 3314.9
```

```
vanwert | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
year |  12390.18   3879.541   3.19   0.050    43.75028   24736.61
year2 |  -866.0179   542.5357  -1.60   0.209   -2592.609   860.5729
_cons |  132911.3   5929.959  22.41   0.000   114039.5   151783.1
```

```
. reg vinton year year2
```

```
Source |  SS  df  MS      Number of obs = 6
-----+-----
Model |  409679697    2   204839849    F( 2,    3) = 10.06
Residual | 61111513.5    3  20370504.5    Prob > F = 0.0468
-----+-----
Total |  470791211    5  94158242.2    R-squared   = 0.8702
                                           Adj R-squared = 0.7837
                                           Root MSE = 4513.4
```

```
vinton | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
year |  1379.164   5282.075   0.26   0.811   -15430.76   18189.08
year2 |  486.6786   738.6735   0.66   0.557   -1864.11   2837.467
_cons |  88819.8    8073.761  11.00   0.002   63125.49   114514.1
```

```
. reg warren year year2
```

```
Source |  SS  df  MS      Number of obs = 6
-----+-----
Model |  1.2051e+09    2   602543938    F( 2,    3) = 10.11
Residual | 178774784    3  59591594.6    Prob > F = 0.0464
-----+-----
Total |  1.3839e+09    5  276772532    R-squared   = 0.8708
                                           Adj R-squared = 0.7847
                                           Root MSE = 7719.6
```

```
warren | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
year |  -39614.56   9034.335  -4.38   0.022   -68365.85  -10863.28
year2 |  5680.554   1263.409   4.50   0.021   1659.821   9701.286
_cons |  294488.9   13809.17  21.33   0.000   250542    338435.8
```

```
. reg washington year year2
```

```
Source |  SS  df  MS      Number of obs = 6
-----+-----
Model |  3.9184e+09    2  1.9592e+09    F( 2,    3) = 30.25
Residual | 194297978    3  64765992.6    Prob > F = 0.0103
-----+-----
Total |  4.1127e+09    5  822543378    R-squared   = 0.9528
                                           Adj R-squared = 0.9213
                                           Root MSE = 8047.7
```

```
-----
```

washington	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	52150.09	9418.401	5.54	0.012	22176.53	82123.64
year2	-8608.857	1317.119	-6.54	0.007	-12800.52	-4417.196
_cons	497035.2	14396.22	34.53	0.000	451220	542850.4

```
-----
```

. reg wayne year year2

```
-----
```

Source	SS	df	MS	Number of obs = 6		
Model	1.0279e+10	2	5.1395e+09	F(2, 3) =	5.63	
Residual	2.7373e+09	3	912424414	Prob > F =	0.0964	
Total	1.3016e+10	5	2.6033e+09	R-squared =	0.7897	
				Adj R-squared =	0.6495	
				Root MSE =	30206	

```
-----
```

```
-----
```

wayne	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	117884.6	35351.03	3.33	0.045	5381.88	230387.4
year2	-15752.84	4943.677	-3.19	0.050	-31485.83	-19.85353
_cons	628048.3	54034.79	11.62	0.001	456085.5	800011.1

```
-----
```

. reg williams year year2

```
-----
```

Source	SS	df	MS	Number of obs = 6		
Model	2.9127e+09	2	1.4564e+09	F(2, 3) =	13.84	
Residual	315608176	3	105202725	Prob > F =	0.0306	
Total	3.2283e+09	5	645666675	R-squared =	0.9022	
				Adj R-squared =	0.8371	
				Root MSE =	10257	

```
-----
```

```
-----
```

williams	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	19577.53	12003.76	1.63	0.201	-18623.78	57778.84
year2	-964.7857	1678.669	-0.57	0.606	-6307.06	4377.489
_cons	242520.4	18347.99	13.22	0.001	184128.9	300911.9

```
-----
```

. reg wood year year2

```
-----
```

Source	SS	df	MS	Number of obs = 6		
Model	460180767	2	230090383	F(2, 3) =	1.02	
Residual	674466633	3	224822211	Prob > F =	0.4583	
Total	1.1346e+09	5	226929480	R-squared =	0.4056	
				Adj R-squared =	0.0093	
				Root MSE =	14994	

```
-----
```

```
-----
```

wood	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
year	5657.396	17547.82	0.32	0.768	-50187.61	61502.4
year2	-75.80357	2453.981	-0.03	0.977	-7885.467	7733.86
_cons	630583.3	26822.21	23.51	0.000	545223	715943.6

```
-----
```

. reg wyandot year year2

```
-----
```

Source	SS	df	MS	Number of obs = 6		
				F(2, 3) =	34.85	

```
-----
```

```

Model | 962768265 2 481384132 Prob > F = 0.0084
Residual | 41441990.8 3 13813996.9 R-squared = 0.9587
-----+-----
Total | 1.0042e+09 5 200842051 Root MSE = 3716.7
Adj R-squared = 0.9312

```

```

-----+-----
wyandot | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
year | -4989.421 4349.74 -1.15 0.335 -18832.24 8853.394
year2 | 1710.464 608.2909 2.81 0.067 -225.3887 3646.317
_cons | 131251.6 6648.668 19.74 0.000 110092.6 152410.6
-----+-----

```

County Lag Forecasts

. reg adams var2

```

Source | SS df MS Number of obs = 5
-----+-----
Model | 213474041 1 213474041 Prob > F = 0.0302
Residual | 42460142.2 3 14153380.7 R-squared = 0.8341
-----+-----
Total | 255934183 4 63983545.7 Root MSE = 3762.1
Adj R-squared = 0.7788

```

```

-----+-----
adams | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
var2 | .8451113 .2176063 3.88 0.030 .1525909 1.537632
_cons | 25777.55 28377.82 0.91 0.431 -64533.34 116088.4
-----+-----

```

. reg allen var4

```

Source | SS df MS Number of obs = 5
-----+-----
Model | 736372349 1 736372349 Prob > F = 0.3159
Residual | 1.5313e+09 3 510417310 R-squared = 0.3247
-----+-----
Total | 2.2676e+09 4 566906070 Root MSE = 22592
Adj R-squared = 0.0996

```

```

-----+-----
allen | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
var4 | .5269046 .4386781 1.20 0.316 -.8691648 1.922974
_cons | 165793.8 163892.7 1.01 0.386 -355785.8 687373.5
-----+-----

```

. reg ashland var6

```

Source | SS df MS Number of obs = 5
-----+-----
Model | 1675188.99 1 1675188.99 Prob > F = 0.9401
Residual | 753872224 3 251290741 R-squared = 0.0022
-----+-----
Total | 755547413 4 188886853 Root MSE = 15852
Adj R-squared = -0.3304

```

```

-----+-----
ashland | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
var6 | -.1145754 1.403291 -0.08 0.940 -4.580473 4.351322
_cons | 362115.8 445720.7 0.81 0.476 -1056366 1780598
-----+-----

```

. reg ashtabula var8

Source	SS	df	MS	Number of obs = 5			
Model	349057110	1	349057110	1	349057110	F(1, 3) =	0.78
Residual	1.3366e+09	3	445519974	3	445519974	Prob > F =	0.4413
						R-squared =	0.2071
						Adj R-squared =	-0.0572
Total	1.6856e+09	4	421404258	4	421404258	Root MSE =	21107

ashtabula	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
var8	1.064861	1.203034	0.89	0.441	-2.763732	4.893453
_cons	-10797.06	316927	-0.03	0.975	-1019400	997806.2

. reg athens var10

Source	SS	df	MS	Number of obs = 5			
Model	10294675	1	10294675	1	10294675	F(1, 3) =	3.27
Residual	9443071.78	3	3147690.59	3	3147690.59	Prob > F =	0.1682
						R-squared =	0.5216
						Adj R-squared =	0.3621
Total	19737746.8	4	4934436.7	4	4934436.7	Root MSE =	1774.2

athens	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
var10	-1.28434	.7101818	-1.81	0.168	-3.544455	.975776
_cons	226633.1	70124.29	3.23	0.048	3466.274	449799.9

. reg auglaize var12

Source	SS	df	MS	Number of obs = 5			
Model	65119793.7	1	65119793.7	1	65119793.7	F(1, 3) =	0.82
Residual	237574272	3	79191423.8	3	79191423.8	Prob > F =	0.4314
						R-squared =	0.2151
						Adj R-squared =	-0.0465
Total	302694065	4	75673516.3	4	75673516.3	Root MSE =	8899

auglaize	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
var12	.3687857	.4066836	0.91	0.431	-.9254631	1.663035
_cons	156303.2	98761.51	1.58	0.212	-158000	470606.4

. reg belmont var14

Source	SS	df	MS	Number of obs = 5			
Model	3.3219e+09	1	3.3219e+09	1	3.3219e+09	F(1, 3) =	4.20
Residual	2.3729e+09	3	790960991	3	790960991	Prob > F =	0.1328
						R-squared =	0.5833
						Adj R-squared =	0.4444
Total	5.6948e+09	4	1.4237e+09	4	1.4237e+09	Root MSE =	28124

belmont	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
var14	1.919005	.9363993	2.05	0.133	-1.061035	4.899046
_cons	-300596.9	325056	-0.92	0.423	-1335070	733876.3

. reg brown var16

```
Source | SS df MS Number of obs = 5
-----+-----
Model | 3321160.24 1 3321160.24 Prob > F = 0.9125
Residual | 698185131 3 232728377 R-squared = 0.0047
-----+-----
Total | 701506291 4 175376573 Adj R-squared = -0.3270
Root MSE = 15255
```

```
-----+-----
brown | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
var16 | -.0652739 .5464107 -0.12 0.912 -1.804197 1.673649
_cons | 184988.1 91570.23 2.02 0.137 -106429.2 476405.5
```

. reg butler var18

```
Source | SS df MS Number of obs = 5
-----+-----
Model | 439324205 1 439324205 Prob > F = 0.8300
Residual | 2.4046e+10 3 8.0154e+09 R-squared = 0.0179
-----+-----
Total | 2.4485e+10 4 6.1213e+09 Adj R-squared = -0.3094
Root MSE = 89529
```

```
-----+-----
butler | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
var18 | -.080704 .3447181 -0.23 0.830 -1.177751 1.016343
_cons | 1097472 338192.4 3.25 0.048 21192.62 2173751
```

. reg carroll var20

```
Source | SS df MS Number of obs = 5
-----+-----
Model | 10028.9479 1 10028.9479 Prob > F = 0.9638
Residual | 12403175.9 3 4134391.95 R-squared = 0.0008
-----+-----
Total | 12413204.8 4 3103301.2 Adj R-squared = -0.3323
Root MSE = 2033.3
```

```
-----+-----
carroll | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
var20 | -.0113779 .231015 -0.05 0.964 -.7465707 .7238149
_cons | 169225.5 38114.88 4.44 0.021 47926.94 290524
```

. reg champaign var22

```
Source | SS df MS Number of obs = 5
-----+-----
Model | 136346627 1 136346627 Prob > F = 0.1897
Residual | 143292040 3 47764013.4 R-squared = 0.4876
-----+-----
Total | 279638667 4 69909666.8 Adj R-squared = 0.3168
Root MSE = 6911.2
```

```
-----+-----
champaign | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
var22 | 1.136514 .6726713 1.69 0.190 -1.004227 3.277254
```

```
_cons | -13762.21      85761.7      -0.16      0.883      -286694.2      259169.8
```

```
. reg clark var24
```

```
Source | SS df MS      Number of obs = 5
-----+-----
Model | 1.1813e+10      1 1.1813e+10      Prob > F = 0.1680
Residual | 1.0819e+10      3 3.6064e+09      R-squared = 0.5220
-----+-----
Total | 2.2632e+10      4 5.6581e+09      Adj R-squared = 0.3626
Root MSE = 60053
F( 1, 3) = 3.28
```

```
clark | Coef.      Std. Err. t      P>|t|      [95% Conf. Interval]
-----+-----
var24 | .6674239    .3687735    1.81    0.168      -.506178    1.841026
_cons | 70827.51    111352.9    0.64    0.570      -283547    425202
```

```
. reg clermont var26
```

```
Source | SS df MS      Number of obs = 5
-----+-----
Model | 1.6187e+09      1 1.6187e+09      Prob > F = 0.2706
Residual | 2.6744e+09      3 891459299      R-squared = 0.3770
-----+-----
Total | 4.2930e+09      4 1.0733e+09      Adj R-squared = 0.1694
Root MSE = 29857
F( 1, 3) = 1.82
```

```
clermont | Coef.      Std. Err. t      P>|t|      [95% Conf. Interval]
-----+-----
var26 | .6722504    .4988904    1.35    0.271      -.9154416    2.259942
_cons | 150576.2    210726.7    0.71    0.526      -520050.3    821202.7
```

```
. reg clinton var28
```

```
Source | SS df MS      Number of obs = 5
-----+-----
Model | 21712036.5      1 21712036.5      Prob > F = 0.2917
Residual | 39987088.7      3 13329029.6      R-squared = 0.3519
-----+-----
Total | 61699125.2      4 15424781.3      Adj R-squared = 0.1359
Root MSE = 3650.9
F( 1, 3) = 1.63
```

```
clinton | Coef.      Std. Err. t      P>|t|      [95% Conf. Interval]
-----+-----
var28 | .310634     .2433873    1.28    0.292      -.4639331    1.085201
_cons | 109760.5    37919.91    2.89    0.063      -10917.59    230438.6
```

```
. reg columbiana var30
```

```
Source | SS df MS      Number of obs = 5
-----+-----
Model | 1.0775e+09      1 1.0775e+09      Prob > F = 0.4755
Residual | 4.8840e+09      3 1.6280e+09      R-squared = 0.1807
-----+-----
Total | 5.9615e+09      4 1.4904e+09      Adj R-squared = -0.0923
Root MSE = 40348
F( 1, 3) = 0.66
```

```
columbiana | Coef.      Std. Err. t      P>|t|      [95% Conf. Interval]
```

var30		.5847802	.71881	0.81	0.475	-1.702794	2.872354
_cons		258534.7	435584.1	0.59	0.595	-1127688	1644758

. reg coshocton var32

Source		SS	df	MS	Number of obs = 5		
Model		79795605.7	1	79795605.7		F(1, 3) = 1.37	
Residual		174170080	3	58056693.2		Prob > F = 0.3257	
Total		253965685	4	63491421.3		R-squared = 0.3142	
						Adj R-squared = 0.0856	
						Root MSE = 7619.5	

coshocton		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
var32		-.5060399	.4316398	-1.17	0.326	-1.87971 .8676305
_cons		251902.7	71720.94	3.51	0.039	23654.63 480150.7

. reg crawford var34

Source		SS	df	MS	Number of obs = 5		
Model		8075770.44	1	8075770.44		F(1, 3) = 1.03	
Residual		23444504.8	3	7814834.92		Prob > F = 0.3842	
Total		31520275.2	4	7880068.8		R-squared = 0.2562	
						Adj R-squared = 0.0083	
						Root MSE = 2795.5	

crawford		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
var34		.35149	.3457649	1.02	0.384	-.7488882 1.451868
_cons		68112.6	35248.7	1.93	0.149	-44064.5 180289.7

. reg cuyahoga var36

Source		SS	df	MS	Number of obs = 5		
Model		7.9116e+10	1	7.9116e+10		F(1, 3) = 29.27	
Residual		8.1087e+09	3	2.7029e+09		Prob > F = 0.0124	
Total		8.7225e+10	4	2.1806e+10		R-squared = 0.9070	
						Adj R-squared = 0.8760	
						Root MSE = 51989	

cuyahoga		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
var36		.8724783	.1612639	5.41	0.012	.3592645 1.385692
_cons		287348.9	225008.8	1.28	0.291	-428729.4 1003427

. reg darke var38

Source		SS	df	MS	Number of obs = 5		
Model		2.0599e+09	1	2.0599e+09		F(1, 3) = 6.57	
Residual		940745750	3	313581917		Prob > F = 0.0830	
Total		3.0006e+09	4	750160646		R-squared = 0.6865	
						Adj R-squared = 0.5820	
						Root MSE = 17708	

darke		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
-------	--	-------	-----------	---	------	----------------------

var38		.9401092	.3668015	2.56	0.083	-.2272168	2.107435
_cons		46642.95	197386.1	0.24	0.828	-581527.7	674813.6

. reg defiance var40

Source		SS	df	MS	Number of obs = 5		
Model		1.8249e+10	1	1.8249e+10		F(1, 3) =	19.25
Residual		2.8433e+09	3	947767764		Prob > F =	0.0219
Total		2.1092e+10	4	5.2730e+09		R-squared =	0.8652
						Adj R-squared =	0.8203
						Root MSE =	30786

defiance		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
var40		1.353839	.3085338	4.39	0.022	.371947	2.335732
_cons		-37579.94	69700.22	-0.54	0.627	-259397.1	184237.3

. reg delaware var42

Source		SS	df	MS	Number of obs = 5		
Model		29991809.3	1	29991809.3		F(1, 3) =	1.55
Residual		58093883.9	3	19364628		Prob > F =	0.3017
Total		88085693.2	4	22021423.3		R-squared =	0.3405
						Adj R-squared =	0.1206
						Root MSE =	4400.5

delaware		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
var42		.5721879	.4597713	1.24	0.302	-.8910097	2.035386
_cons		72682.38	74499.94	0.98	0.401	-164409.7	309774.5

. reg erie var44

Source		SS	df	MS	Number of obs = 5		
Model		317658965	1	317658965		F(1, 3) =	4.69
Residual		203289896	3	67763298.5		Prob > F =	0.1190
Total		520948861	4	130237215		R-squared =	0.6098
						Adj R-squared =	0.4797
						Root MSE =	8231.8

erie		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
var44		.7344408	.3392138	2.17	0.119	-.3450889	1.81397
_cons		49640.95	52221.22	0.95	0.412	-116550.3	215832.2

. reg fairfield var46

Source		SS	df	MS	Number of obs = 5		
Model		128876887	1	128876887		F(1, 3) =	3.06
Residual		126420968	3	42140322.6		Prob > F =	0.1786
Total		255297855	4	63824463.7		R-squared =	0.5048
						Adj R-squared =	0.3397
						Root MSE =	6491.6

fairfield	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
var46	.6441588	.3683447	1.75	0.179	-.5280783	1.816396
_cons	73058.8	68837.45	1.06	0.366	-146012.7	292130.3

. reg fayette var48

Source	SS	df	MS	Number of obs = 5		
Model	29744037.9	1	29744037.9		F(1, 3) =	1.18
Residual	75848289.3	3	25282763.1		Prob > F =	0.3575
					R-squared =	0.2817
					Adj R-squared =	0.0422
Total	105592327	4	26398081.8		Root MSE =	5028.2

fayette	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
var48	.4694962	.4328569	1.08	0.357	-.9080477	1.84704
_cons	76529.62	61282.47	1.25	0.300	-118498.6	271557.8

. reg franklin var50

Source	SS	df	MS	Number of obs = 5		
Model	2.3114e+11	1	2.3114e+11		F(1, 3) =	11.25
Residual	6.1644e+10	3	2.0548e+10		Prob > F =	0.0439
					R-squared =	0.7895
					Adj R-squared =	0.7193
Total	2.9278e+11	4	7.3195e+10		Root MSE =	1.4e+05

franklin	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
var50	2.05657	.6131909	3.35	0.044	.1051231	4.008018
_cons	-2314079	1423434	-1.63	0.202	-6844082	2215924

. reg fulton var52

Source	SS	df	MS	Number of obs = 5		
Model	113219608	1	113219608		F(1, 3) =	0.37
Residual	916710073	3	305570024		Prob > F =	0.5857
					R-squared =	0.1099
					Adj R-squared =	-0.1868
Total	1.0299e+09	4	257482420		Root MSE =	17481

fulton	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
var52	-.3428413	.5632325	-0.61	0.586	-2.135299	1.449616
_cons	457213.3	187141	2.44	0.092	-138353	1052779

. reg gallia var54

Source	SS	df	MS	Number of obs = 5		
Model	2861394.78	1	2861394.78		F(1, 3) =	0.09
Residual	93366374	3	31122124.7		Prob > F =	0.7815
					R-squared =	0.0297
					Adj R-squared =	-0.2937
Total	96227768.8	4	24056942.2		Root MSE =	5578.7

```
-----+-----
gallia | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
var54  | -.1627489 .5367398   -0.30  0.782   -1.870894   1.545397
_cons  |  244133.1 111165.6    2.20  0.116   -109645.4   597911.5
-----+-----
```

. reg geauga var56

```
-----+-----
Source | SS   df MS   Number of obs = 5
-----+-----
Model  | 2.3481e+10   1 2.3481e+10   Prob > F = 4.93
Residual | 1.4301e+10   3 4.7669e+09   R-squared = 0.1131
-----+-----
Total  | 3.7781e+10   4 9.4453e+09   Adj R-squared = 0.4953
Root MSE = 69043
```

```
-----+-----
geauga | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
var56  | .6921063 .3118429    2.22  0.113   -.300317    1.68453
_cons  |  62840.1 104838.1    0.60  0.591   -270801.6   396481.8
-----+-----
```

. reg greene var58

```
-----+-----
Source | SS   df MS   Number of obs = 5
-----+-----
Model  | 1.0728e+09   1 1.0728e+09   Prob > F = 1.05
Residual | 3.0630e+09   3 1.0210e+09   R-squared = 0.3808
-----+-----
Total  | 4.1358e+09   4 1.0339e+09   Adj R-squared = 0.2594
Root MSE = 31953
```

```
-----+-----
greene | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
var58  | .6406598 .6250165    1.03  0.381   -1.348422   2.629741
_cons  |  52865.87 131020     0.40  0.714   -364098.4   469830.1
-----+-----
```

. reg guernsey var60

```
-----+-----
Source | SS   df MS   Number of obs = 5
-----+-----
Model  | 851281150   1 851281150   Prob > F = 13.61
Residual | 187680719   3 62560239.7   R-squared = 0.0345
-----+-----
Total  | 1.0390e+09   4 259740467   Adj R-squared = 0.8194
Root MSE = 0.7591
```

```
-----+-----
guernsey | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
var60  |  1.30836 .3546826    3.69  0.035   .1796015    2.437118
_cons  | -41155.88 56203.76   -0.73  0.517   -220021.3   137709.6
-----+-----
```

. reg hamilton var62

```
-----+-----
Source | SS   df MS   Number of obs = 5
-----+-----
Model  | 5.6769e+10   1 5.6769e+10   Prob > F = 6.22
Residual | 2.7391e+10   3 9.1304e+09   R-squared = 0.0882
-----+-----
Total  | 8.4160e+10   4 2.1040e+10   Adj R-squared = 0.5660
Root MSE = 95553
```

```
-----
```

hamilton	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
var62	.8218905	.3296125	2.49	0.088	-.2270836	1.870865
_cons	407470	594094.4	0.69	0.542	-1483204	2298144

```
-----
```

. reg hardin var66

```
-----
```

Source	SS	df	MS	Number of obs = 5		
Model	310959636	1	310959636	F(1, 3) =	21.31	
Residual	43777167.6	3	14592389.2	Prob > F =	0.0191	
				R-squared	= 0.8766	
				Adj R-squared	= 0.8355	
Total	354736803	4	88684200.8	Root MSE =	3820	

```
-----
```

```
-----
```

hardin	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
var66	1.044914	.226356	4.62	0.019	.3245488	1.76528
_cons	-2699.031	38353.11	-0.07	0.948	-124755.8	119357.7

```
-----
```

. reg harrison var68

```
-----
```

Source	SS	df	MS	Number of obs = 5		
Model	134764234	1	134764234	F(1, 3) =	6.00	
Residual	67350123.6	3	22450041.2	Prob > F =	0.0917	
				R-squared	= 0.6668	
				Adj R-squared	= 0.5557	
Total	202114357	4	50528589.3	Root MSE =	4738.1	

```
-----
```

```
-----
```

harrison	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
var68	.6855909	.2798249	2.45	0.092	-.2049367	1.576119
_cons	36854.97	29990.58	1.23	0.307	-58588.44	132298.4

```
-----
```

. reg henry var70

```
-----
```

Source	SS	df	MS	Number of obs = 5		
Model	2587043.67	1	2587043.67	F(1, 3) =	0.25	
Residual	30759845.1	3	10253281.7	Prob > F =	0.6500	
				R-squared	= 0.0776	
				Adj R-squared	= -0.2299	
Total	33346888.8	4	8336722.2	Root MSE =	3202.1	

```
-----
```

```
-----
```

henry	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
var70	.0644064	.1282209	0.50	0.650	-.3436497	.4724625
_cons	299884.3	40458.58	7.41	0.005	171127	428641.5

```
-----
```

. reg highland var72

```
-----
```

Source	SS	df	MS	Number of obs = 5		
Model	249728103	1	249728103	F(1, 3) =	17.81	
Residual	42076715.3	3	14025571.8	Prob > F =	0.0243	
				R-squared	= 0.8558	
				Adj R-squared	= 0.8077	

```
-----
```

Total | 291804818 4 72951204.5 Root MSE = 3745.1

highland	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
var72	.955506	.2264436	4.22	0.024	.2348615	1.676151
_cons	12245.05	34773.09	0.35	0.748	-98418.44	122908.5

. reg hocking var74

Source	SS	df	MS	Number of obs = 5		F(1, 3) =	0.25
Model	8677220.86	1	8677220.86	Prob > F =	0.6541	R-squared =	0.0757
Residual	105922578	3	35307526	Adj R-squared =	-0.2324	Root MSE =	5942
Total	114599799	4	28649949.7				

hocking	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
var74	.2400101	.484142	0.50	0.654	-1.300746	1.780766
_cons	76805.23	47373.23	1.62	0.203	-73957.54	227568

. reg holmes var76

Source	SS	df	MS	Number of obs = 5		F(1, 3) =	9.04
Model	1.8991e+09	1	1.8991e+09	Prob > F =	0.0574	R-squared =	0.7508
Residual	630270736	3	210090245	Adj R-squared =	0.6678	Root MSE =	14494
Total	2.5294e+09	4	632340229				

holmes	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
var76	.8013215	.2665244	3.01	0.057	-.046878	1.649521
_cons	78983.94	81900.22	0.96	0.406	-181659.1	339627

. reg huron var78

Source	SS	df	MS	Number of obs = 5		F(1, 3) =	0.03
Model	625180.997	1	625180.997	Prob > F =	0.8801	R-squared =	0.0089
Residual	69690528.2	3	23230176.1	Adj R-squared =	-0.3215	Root MSE =	4819.8
Total	70315709.2	4	17578927.3				

huron	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
var78	-.039732	.2421941	-0.16	0.880	-.8105016	.7310376
_cons	307168.9	70696.13	4.34	0.023	82182.27	532155.6

. reg jackson var80

Source	SS	df	MS	Number of obs = 5		F(1, 3) =	0.49
Model	30499288.3	1	30499288.3	Prob > F =	0.5337	R-squared =	0.1408
Residual	186098901	3	62032966.8				

```
-----+-----
Total | 216598189      4  54149547.2      Adj R-squared = -0.1456
Root MSE = 7876.1
```

```
-----+-----
jackson | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
var80 | .2942412 .4196333   0.70   0.534   -1.041219   1.629702
_cons | 121902.6 70934.78  1.72   0.184   -103843.5   347648.8
```

```
. reg jefferson var82
```

```
Source | SS   df MS   Number of obs = 5
-----+-----
Model | 4.2493e+09   1  4.2493e+09   F( 1, 3) = 10.62
Residual | 1.2005e+09   3  400178092   Prob > F = 0.0472
Total | 5.4499e+09   4  1.3625e+09   R-squared = 0.7797
Adj R-squared = 0.7063
Root MSE = 20004
```

```
-----+-----
jefferson | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
var82 | 1.298865 .398593   3.26   0.047   .0303642   2.567366
_cons | -40437.67 78636.29 -0.51   0.643   -290693.4   209818.1
```

```
. reg knox var84
```

```
Source | SS   df MS   Number of obs = 5
-----+-----
Model | 390628248   1  390628248   F( 1, 3) = 113.02
Residual | 10368631.3   3  3456210.42   Prob > F = 0.0018
Total | 400996879   4  100249220   R-squared = 0.9741
Adj R-squared = 0.9655
Root MSE = 1859.1
```

```
-----+-----
knox | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
var84 | .9686558 .0911145  10.63   0.002   .6786886   1.258623
_cons | 13229.11 18467.4   0.72   0.526   -45542.39   72000.62
```

```
. reg lake var86
```

```
Source | SS   df MS   Number of obs = 5
-----+-----
Model | 10106628.1   1  10106628.1   F( 1, 3) = 2.01
Residual | 15054686.7   3  5018228.9   Prob > F = 0.2509
Total | 25161314.8   4  6290328.7   R-squared = 0.4017
Adj R-squared = 0.2022
Root MSE = 2240.1
```

```
-----+-----
lake | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
var86 | -.7113538 .5012539  -1.42   0.251   -2.306567   .8838598
_cons | 252219.5 73962.19  3.41   0.042   16838.82   487600.2
```

```
. reg lawrence var88
```

```
Source | SS   df MS   Number of obs = 5
-----+-----
Model | 61821349.1   1  61821349.1   F( 1, 3) = 0.99
Prob > F = 0.3937
```

Residual		187915143	3	62638381	R-squared	=	0.2475
-----					Adj R-squared	=	-0.0033
Total		249736492	4	62434123	Root MSE	=	7914.4

lawrence		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
var88		.2750352	.2768467	0.99	0.394	-.6060146	1.156085
_cons		158961.4	62580.6	2.54	0.085	-40198	358120.8

. reg licking var90

Source		SS	df	MS	Number of obs =	5		
-----					F(1, 3) =	0.06		
Model		4329669.84	1	4329669.84	Prob > F =	0.8277		
Residual		230604659	3	76868219.8	R-squared	=	0.0184	
-----					Adj R-squared	=	-0.3088	
Total		234934329	4	58733582.3	Root MSE	=	8767.5	

licking		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
var90		-.1955497	.8239543	-0.24	0.828	-2.81774	2.426641
_cons		381389.7	259205	1.47	0.238	-443516.3	1206296

. reg logan var92

Source		SS	df	MS	Number of obs =	5		
-----					F(1, 3) =	27.56		
Model		2.5441e+09	1	2.5441e+09	Prob > F =	0.0135		
Residual		276910444	3	92303481.3	R-squared	=	0.9018	
-----					Adj R-squared	=	0.8691	
Total		2.8210e+09	4	705257104	Root MSE	=	9607.5	

logan		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
var92		3.47791	.6624586	5.25	0.013	1.369671	5.586148
_cons		-320419.1	89404.83	-3.58	0.037	-604945.2	-35893.06

. reg lorain var94

Source		SS	df	MS	Number of obs =	5		
-----					F(1, 3) =	15.06		
Model		2.0199e+09	1	2.0199e+09	Prob > F =	0.0303		
Residual		402363776	3	134121259	R-squared	=	0.8339	
-----					Adj R-squared	=	0.7785	
Total		2.4223e+09	4	605573578	Root MSE	=	11581	

lorain		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
var94		.9725153	.2505977	3.88	0.030	.1750017	1.770029
_cons		21376.92	71038.43	0.30	0.783	-204699.1	247452.9

. reg lucas var96

Source		SS	df	MS	Number of obs =	5		
-----					F(1, 3) =	3.31		

```

Model | 2.7610e+09    1  2.7610e+09    Prob > F = 0.1663
Residual | 2.5011e+09    3  833687316    R-squared   = 0.5247
-----+-----
Total | 5.2621e+09    4  1.3155e+09    Root MSE = 28874
Adj R-squared = 0.3663

```

```

-----+-----
lucas | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
var96 |   .8216068   .4514701   1.82   0.166   - .6151724   2.258386
_cons |  167013.2   360107    0.46   0.674   -979008.1   1313035
-----+-----

```

```
. reg madison var98
```

```

Source | SS   df MS   Number of obs = 5
-----+-----
Model | 1.6343e+09    1  1.6343e+09    Prob > F = 0.0486
Residual | 472800141    3  157600047    R-squared   = 0.7756
-----+-----
Total | 2.1071e+09    4  526764728    Adj R-squared = 0.7008
Root MSE = 12554
F( 1, 3) = 10.37

```

```

-----+-----
madison | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
var98 |   .9548818   .2965291   3.22   0.049   .0111937   1.89857
_cons |   21335.2   63371.87   0.34   0.759   -180342.4   223012.8
-----+-----

```

```
. reg mahoning var100
```

```

Source | SS   df MS   Number of obs = 5
-----+-----
Model | 1.1294e+11    1  1.1294e+11    Prob > F = 0.2302
Residual | 1.5025e+11    3  5.0082e+10    R-squared   = 0.4291
-----+-----
Total | 2.6319e+11    4  6.5797e+10    Adj R-squared = 0.2388
Root MSE = 2.2e+05
F( 1, 3) = 2.26

```

```

-----+-----
mahoning | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
var100 |   .5428694   .3615052   1.50   0.230   - .6076015   1.69334
_cons |   823615   553501.6   1.49   0.233   -937874.1   2585104
-----+-----

```

```
. reg marion var102
```

```

Source | SS   df MS   Number of obs = 5
-----+-----
Model | 148377076    1  148377076    Prob > F = 0.1702
Residual | 137879779    3  45959926.3    R-squared   = 0.5183
-----+-----
Total | 286256855    4  71564213.7    Adj R-squared = 0.3578
Root MSE = 6779.4
F( 1, 3) = 3.23

```

```

-----+-----
marion | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
var102 |   .7226491   .4021923   1.80   0.170   - .5573062   2.002604
_cons |  45806.49   58288.03   0.79   0.489   -139692   231305
-----+-----

```

```
. reg medina var104
```

```

Source | SS   df MS   Number of obs = 5

```

```

-----+-----
Model | 4.4597e+09 1 4.4597e+09 Prob > F = 0.0174 F( 1, 3) = 22.90
Residual | 584236981 3 194745660 R-squared = 0.8842
-----+-----
Total | 5.0439e+09 4 1.2610e+09 Root MSE = 13955 Adj R-squared = 0.8456

```

```

-----+-----
medina | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
var104 | .9069731 .1895289 4.79 0.017 .3038076 1.510139
_cons | 63838.19 76475.79 0.83 0.465 -179541.9 307218.3
-----+-----

```

. reg meigs var106

```

Source | SS df MS Number of obs = 5
-----+-----
Model | 45157360.1 1 45157360.1 Prob > F = 0.2079 F( 1, 3) = 2.56
Residual | 52908764.7 3 17636254.9 R-squared = 0.4605
-----+-----
Total | 98066124.8 4 24516531.2 Root MSE = 4199.6 Adj R-squared = 0.2806

```

```

-----+-----
meigs | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
var106 | .9432847 .5894972 1.60 0.208 -.9327583 2.819328
_cons | 9730.206 63327.23 0.15 0.888 -191805.3 211265.7
-----+-----

```

. reg mercer var108

```

Source | SS df MS Number of obs = 5
-----+-----
Model | 1.2061e+10 1 1.2061e+10 Prob > F = 0.1094 F( 1, 3) = 5.09
Residual | 7.1119e+09 3 2.3706e+09 R-squared = 0.6291
-----+-----
Total | 1.9173e+10 4 4.7933e+09 Root MSE = 48689 Adj R-squared = 0.5054

```

```

-----+-----
mercer | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
var108 | .7692567 .341041 2.26 0.109 -.3160879 1.854601
_cons | 157880.6 184918.5 0.85 0.456 -430612.8 746373.9
-----+-----

```

. reg miami var110

```

Source | SS df MS Number of obs = 5
-----+-----
Model | 905868763 1 905868763 Prob > F = 0.2108 F( 1, 3) = 2.52
Residual | 1.0797e+09 3 359896713 R-squared = 0.4562
-----+-----
Total | 1.9856e+09 4 496389726 Root MSE = 18971 Adj R-squared = 0.2750

```

```

-----+-----
miami | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
var110 | .6499972 .4097017 1.59 0.211 -.6538565 1.953851
_cons | 122961.1 128706.3 0.96 0.410 -286639.6 532561.9
-----+-----

```

. reg monroe var112

```

Source | SS df MS      Number of obs = 5
-----+-----
Model | 38302755.7    1 38302755.7    Prob > F = 0.4120
Residual | 127169865    3 42389955.2    R-squared = 0.2315
-----+-----
Total | 165472621    4 41368155.3    Adj R-squared = -0.0247
Root MSE = 6510.8

```

```

-----+-----
monroe | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
var112 | .4362146 .4588985    0.95  0.412   -1.024205   1.896634
_cons  | 74432.73 56662.74    1.31  0.280   -105893.4   254758.9

```

```
. reg montgomery var114
```

```

Source | SS df MS      Number of obs = 5
-----+-----
Model | 2.2312e+10    1 2.2312e+10    Prob > F = 0.0367
Residual | 5.1538e+09    3 1.7179e+09    R-squared = 0.8124
-----+-----
Total | 2.7466e+10    4 6.8665e+09    Adj R-squared = 0.7498
Root MSE = 41448

```

```

-----+-----
montgomery | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
var114 | 1.22029 .3386045    3.60  0.037   .1426994   2.297881
_cons  | -147043.2 286645.6   -0.51  0.643   -1059278   765191.1

```

```
. reg morgan var116
```

```

Source | SS df MS      Number of obs = 5
-----+-----
Model | 94763805.9    1 94763805.9    Prob > F = 0.0283
Residual | 17899311.3    3 5966437.11    R-squared = 0.8411
-----+-----
Total | 112663117    4 28165779.3    Adj R-squared = 0.7882
Root MSE = 2442.6

```

```

-----+-----
morgan | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
var116 | .9044979 .2269571    3.99  0.028   .182219   1.626777
_cons  | 11967.29 20008.97    0.60  0.592   -51710.17  75644.76

```

```
. reg morrow var118
```

```

Source | SS df MS      Number of obs = 5
-----+-----
Model | 37970337.4    1 37970337.4    Prob > F = 0.2714
Residual | 63020385.4    3 21006795.1    R-squared = 0.3760
-----+-----
Total | 100990723    4 25247680.7    Adj R-squared = 0.1680
Root MSE = 4583.3

```

```

-----+-----
morrow | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
var118 | .486919 .3621716    1.34  0.271   -.6656727  1.639511
_cons  | 68822.65 47622.62    1.45  0.244   -82733.77  220379.1

```

```
. reg muskingum var120
```

```

Source | SS df MS      Number of obs = 5
-----+-----
Model | 123418580      1 123418580      Prob > F = 0.6865
Residual | 1.8695e+09      3 623170704      R-squared = 0.0619
-----+-----
Total | 1.9929e+09      4 498232673      Adj R-squared = -0.2508
Root MSE = 24963

```

```

-----+-----
muskingum | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
var120 |   .5101703   1.14638   0.45   0.686   -3.138121   4.158462
_cons | 139055.4   304626.4   0.46   0.679   -830401.8   1108513
-----+-----

```

. reg noble var122

```

Source | SS df MS      Number of obs = 5
-----+-----
Model | 584379316      1 584379316      Prob > F = 0.0112
Residual | 55653097.1      3 18551032.4      R-squared = 0.9130
-----+-----
Total | 640032413      4 160008103      Adj R-squared = 0.8841
Root MSE = 4307.1

```

```

-----+-----
noble | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
var122 | 1.286552   .2292261   5.61   0.011   .5570524   2.016052
_cons | -28852.32  28015.05  -1.03   0.379  -118008.7   60304.08
-----+-----

```

. reg ottawa var124

```

Source | SS df MS      Number of obs = 5
-----+-----
Model | 18066582.6      1 18066582.6      Prob > F = 0.4367
Residual | 67659800.2      3 22553266.7      R-squared = 0.2107
-----+-----
Total | 85726382.8      4 21431595.7      Adj R-squared = -0.0523
Root MSE = 4749

```

```

-----+-----
ottawa | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
var124 | .4090215   .4569965   0.90   0.437   -1.045345   1.863388
_cons | 86895.79   63885.22   1.36   0.267  -116415.5   290207.1
-----+-----

```

. reg paulding var126

```

Source | SS df MS      Number of obs = 5
-----+-----
Model | 309411276      1 309411276      Prob > F = 0.2088
Residual | 364384569      3 121461523      R-squared = 0.4592
-----+-----
Total | 673795845      4 168448961      Adj R-squared = 0.2789
Root MSE = 11021

```

```

-----+-----
paulding | Coef.   Std. Err. t    P>|t|    [95% Conf. Interval]
-----+-----
var126 | .5264458   .3298412   1.60   0.209   -.5232562   1.576148
_cons | 72611     47506.65   1.53   0.224  -78576.36   223798.4
-----+-----

```

. reg perry var128

Source	SS	df	MS	Number of obs = 5			
Model	6214626.53	1	6214626.53	F(1, 3) =	1.59	Prob > F =	0.2970
Residual	11759900.3	3	3919966.76	R-squared =	0.3457	Adj R-squared =	0.1277
Total	17974526.8	4	4493631.7	Root MSE =	1979.9		

perry	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
var128	1.280169	1.016719	1.26	0.297	-1.955485	4.515822
_cons	-28440.45	106877.9	-0.27	0.807	-368573.7	311692.8

. reg pickaway var130

Source	SS	df	MS	Number of obs = 5			
Model	2153030.98	1	2153030.98	F(1, 3) =	0.18	Prob > F =	0.6981
Residual	35406872.2	3	11802290.7	R-squared =	0.0573	Adj R-squared =	-0.2569
Total	37559903.2	4	9389975.8	Root MSE =	3435.4		

pickaway	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
var130	-.2052576	.4805707	-0.43	0.698	-1.734648	1.324133
_cons	151540	60294.96	2.51	0.087	-40345.53	343425.4

. reg pike var132

Source	SS	df	MS	Number of obs = 5			
Model	395574061	1	395574061	F(1, 3) =	12.85	Prob > F =	0.0372
Residual	92370932	3	30790310.7	R-squared =	0.8107	Adj R-squared =	0.7476
Total	487944993	4	121986248	Root MSE =	5548.9		

pike	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
var132	.7819427	.2181565	3.58	0.037	.0876715	1.476214
_cons	39260.61	32531.33	1.21	0.314	-64268.62	142789.8

. reg portage var134

Source	SS	df	MS	Number of obs = 5			
Model	4.7315e+09	1	4.7315e+09	F(1, 3) =	6.98	Prob > F =	0.0775
Residual	2.0322e+09	3	677391807	R-squared =	0.6995	Adj R-squared =	0.5994
Total	6.7636e+09	4	1.6909e+09	Root MSE =	26027		

portage	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
var134	.8133101	.307736	2.64	0.077	-.1660433	1.792664
_cons	128483.7	167366.7	0.77	0.499	-404151.7	661119.2

. reg preble var136

Source	SS	df	MS	Number of obs = 5			
Model	72825.0349	1	72825.0349			F(1, 3) =	0.00
Residual	347249844	3	115749948			Prob > F =	0.9816
						R-squared =	0.0002
						Adj R-squared =	-0.3331
Total	347322669	4	86830667.3			Root MSE =	10759

preble	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
var136	-.0134676	.5369204	-0.03	0.982	-1.722188	1.695253
_cons	271954.2	143190.6	1.90	0.154	-183742	727650.5

. reg putnam var138

Source	SS	df	MS	Number of obs = 5			
Model	12232505.6	1	12232505.6			F(1, 3) =	0.19
Residual	189363049	3	63121016.4			Prob > F =	0.6896
						R-squared =	0.0607
						Adj R-squared =	-0.2524
Total	201595555	4	50398888.7			Root MSE =	7944.9

putnam	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
var138	-.1833898	.4165858	-0.44	0.690	-1.509152	1.142372
_cons	258476.9	88636.13	2.92	0.062	-23602.8	540556.6

. reg richland var140

Source	SS	df	MS	Number of obs = 5			
Model	2898931.7	1	2898931.7			F(1, 3) =	0.12
Residual	72672215.1	3	24224071.7			Prob > F =	0.7522
						R-squared =	0.0384
						Adj R-squared =	-0.2822
Total	75571146.8	4	18892786.7			Root MSE =	4921.8

richland	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
var140	.1833487	.530008	0.35	0.752	-1.503373	1.870071
_cons	163540.9	105900.7	1.54	0.220	-173482.3	500564.1

. reg ross var142

Source	SS	df	MS	Number of obs = 5			
Model	64304095.9	1	64304095.9			F(1, 3) =	0.48
Residual	398880953	3	132960318			Prob > F =	0.5368
						R-squared =	0.1388
						Adj R-squared =	-0.1482
Total	463185049	4	115796262			Root MSE =	11531

ross	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
var142	1.062896	1.528384	0.70	0.537	-3.801105	5.926898
_cons	-5544.636	283537.1	-0.02	0.986	-907886.4	896797.1

. reg sandusky var144

Source	SS	df	MS	Number of obs = 5			
Model	7824729.9	1	7824729.9			F(1, 3) = 0.50	Prob > F = 0.5295
Residual	46713954.9	3	15571318.3			R-squared = 0.1435	Adj R-squared = -0.1420
Total	54538684.8	4	13634671.2			Root MSE = 3946.1	

sandusky	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
var144	-.1772132	.2499909	-0.71	0.530	-.9727958	.6183693
_cons	254720	53151.52	4.79	0.017	85568.16	423871.9

. reg scioto var146

Source	SS	df	MS	Number of obs = 5			
Model	535.7694	1	535.7694			F(1, 3) = 0.00	Prob > F = 0.9959
Residual	51933065.4	3	17311021.8			R-squared = 0.0000	Adj R-squared = -0.3333
Total	51933601.2	4	12983400.3			Root MSE = 4160.7	

scioto	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
var146	-.0024309	.4369554	-0.01	0.996	-1.393018	1.388156
_cons	272574.7	117957.9	2.31	0.104	-102820.1	647969.6

. reg seneca var148

Source	SS	df	MS	Number of obs = 5			
Model	237091.673	1	237091.673			F(1, 3) = 0.01	Prob > F = 0.9363
Residual	94528777.1	3	31509592.4			R-squared = 0.0025	Adj R-squared = -0.3300
Total	94765868.8	4	23691467.2			Root MSE = 5613.3	

seneca	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
var148	.0376097	.4335735	0.09	0.936	-1.342215	1.417434
_cons	220502.7	98800.28	2.23	0.112	-93923.9	534929.3

. reg shelby var150

Source	SS	df	MS	Number of obs = 5			
Model	550000223	1	550000223			F(1, 3) = 1.32	Prob > F = 0.3343
Residual	1.2527e+09	3	417570774			R-squared = 0.3051	Adj R-squared = 0.0735
Total	1.8027e+09	4	450678136			Root MSE = 20435	

shelby	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
var150	.5048524	.439894	1.15	0.334	-.8950867	1.904792

```

_cons | 259542.4 236917.3 1.10 0.353 -494434.3 1013519
-----

```

```
. reg stark var152
```

```

Source | SS df MS Number of obs = 5
-----+-----
Model | 1.4988e+09 1 1.4988e+09 Prob > F = 0.1415
Residual | 1.1423e+09 3 380755511 R-squared = 0.5675
-----+-----
Total | 2.6410e+09 4 660262198 Adj R-squared = 0.4233
Root MSE = 19513
F( 1, 3) = 3.94

```

```

stark | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
var152 | .9587354 .4832285 1.98 0.142 -.5791135 2.496584
_cons | 47542.22 353342.9 0.13 0.901 -1076953 1172037
-----

```

```
. reg summit var154
```

```

Source | SS df MS Number of obs = 5
-----+-----
Model | 1.5573e+11 1 1.5573e+11 Prob > F = 0.0399
Residual | 3.8462e+10 3 1.2821e+10 R-squared = 0.8019
-----+-----
Total | 1.9419e+11 4 4.8548e+10 Adj R-squared = 0.7359
Root MSE = 1.1e+05
F( 1, 3) = 12.15

```

```

summit | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
var154 | .8799471 .252477 3.49 0.040 .0764527 1.683442
_cons | 284005 388267.1 0.73 0.517 -951634.1 1519644
-----

```

```
. reg trumbull var156
```

```

Source | SS df MS Number of obs = 5
-----+-----
Model | 2.4878e+10 1 2.4878e+10 Prob > F = 0.0760
Residual | 1.0505e+10 3 3.5016e+09 R-squared = 0.7031
-----+-----
Total | 3.5383e+10 4 8.8457e+09 Adj R-squared = 0.6041
Root MSE = 59175
F( 1, 3) = 7.10

```

```

trumbull | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----
var156 | .780132 .2926825 2.67 0.076 -.1513144 1.711578
_cons | 362678.7 397749.3 0.91 0.429 -903137.3 1628495
-----

```

```
. reg tuscarawas var158
```

```

Source | SS df MS Number of obs = 5
-----+-----
Model | 3.6872e+09 1 3.6872e+09 Prob > F = 0.0059
Residual | 224704154 3 74901384.7 R-squared = 0.9426
-----+-----
Total | 3.9119e+09 4 977986121 Adj R-squared = 0.9234
Root MSE = 8654.6
F( 1, 3) = 49.23

```

```

tuscarawas | Coef. Std. Err. t P>|t| [95% Conf. Interval]
-----+-----

```

var158		1.611634	.2296998	7.02	0.006	.8806266	2.342641
_cons		-229359.5	92689.45	-2.47	0.090	-524338.7	65619.75

. reg union var160

Source		SS	df	MS	Number of obs = 5		
Model		1.4129e+09	1	1.4129e+09		F(1, 3) =	11.17
Residual		379324599	3	126441533		Prob > F =	0.0443
Total		1.7923e+09	4	448066920		R-squared =	0.7884
						Adj R-squared =	0.7178
						Root MSE =	11245

union		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
var160		1.186735	.3550064	3.34	0.044	.0569459 2.316523
_cons		-39222.3	96603.53	-0.41	0.712	-346657.8 268213.2

. reg vanwert var162

Source		SS	df	MS	Number of obs = 5		
Model		281707857	1	281707857		F(1, 3) =	11.95
Residual		70738467.2	3	23579489.1		Prob > F =	0.0407
Total		352446324	4	88111581		R-squared =	0.7993
						Adj R-squared =	0.7324
						Root MSE =	4855.9

vanwert		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
var162		.7428284	.2149098	3.46	0.041	.0588895 1.426767
_cons		47798.78	34507.4	1.39	0.260	-62019.15 157616.7

. reg vinton var164

Source		SS	df	MS	Number of obs = 5		
Model		142873541	1	142873541		F(1, 3) =	3.38
Residual		126700569	3	42233522.9		Prob > F =	0.1632
Total		269574110	4	67393527.5		R-squared =	0.5300
						Adj R-squared =	0.3733
						Root MSE =	6498.7

vinton		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
var164		.9904556	.5385026	1.84	0.163	-.7232999 2.704211
_cons		6814.83	52711.27	0.13	0.905	-160936 174565.6

. reg warren var166

Source		SS	df	MS	Number of obs = 5		
Model		53248514.4	1	53248514.4		F(1, 3) =	0.17
Residual		935045742	3	311681914		Prob > F =	0.7071
Total		988294257	4	247073564		R-squared =	0.0539
						Adj R-squared =	-0.2615
						Root MSE =	17655

warren		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
--------	--	-------	-----------	---	------	----------------------

var166		-.27002	.653278	-0.41	0.707	-2.349042	1.809002
_cons		302444.5	155240.5	1.95	0.147	-191600.1	796489

. reg washington var168

Source		SS	df	MS	Number of obs = 5		
Model		921072709	1	921072709		F(1, 3) =	0.91
Residual		3.0420e+09	3	1.0140e+09		Prob > F =	0.4109
Total		3.9631e+09	4	990769773		R-squared =	0.2324
						Adj R-squared =	-0.0234
						Root MSE =	31843

washington		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
var168		.7210154	.7565141	0.95	0.411	-1.68655	3.128581
_cons		149024.8	422243.7	0.35	0.747	-1194743	1492793

. reg wayne var170

Source		SS	df	MS	Number of obs = 5		
Model		593166.247	1	593166.247		F(1, 3) =	0.00
Residual		3.0902e+09	3	1.0301e+09		Prob > F =	0.9824
Total		3.0908e+09	4	772706632		R-squared =	0.0002
						Adj R-squared =	-0.3331
						Root MSE =	32095

wayne		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
var170		.0068376	.2849391	0.02	0.982	-.8999657	.913641
_cons		814411.2	229835.6	3.54	0.038	82971.68	1545851

. reg williams var172

Source		SS	df	MS	Number of obs = 5		
Model		796850620	1	796850620		F(1, 3) =	4.00
Residual		597927214	3	199309071		Prob > F =	0.1394
Total		1.3948e+09	4	348694459		R-squared =	0.5713
						Adj R-squared =	0.4284
						Root MSE =	14118

williams		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
var172		.5741064	.2871227	2.00	0.139	-.339646	1.487859
_cons		137041	83851.25	1.63	0.201	-129811.1	403893.1

. reg wood var174

Source		SS	df	MS	Number of obs = 5		
Model		24432237.1	1	24432237.1		F(1, 3) =	0.10
Residual		718580414	3	239526805		Prob > F =	0.7704
Total		743012651	4	185753163		R-squared =	0.0329
						Adj R-squared =	-0.2895
						Root MSE =	15477

wood	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
var174	-.1556757	.4874345	-0.32	0.770	-1.70691	1.395559
_cons	753598	315534.3	2.39	0.097	-250573	1757769

. reg wyandot var176

Source	SS	df	MS	Number of obs = 5		F(1, 3) = 30.45
Model	698524946	1	698524946	Prob > F = 0.0117		
Residual	68813549.1	3	22937849.7	R-squared = 0.9103		
Total	767338495	4	191834624	Adj R-squared = 0.8804	Root MSE = 4789.3	

wyandot	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
var176	1.819024	.3296278	5.52	0.012	.7700013	2.868047
_cons	-102280	44415.95	-2.30	0.105	-243631.4	39071.35