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RENEWABLE PORTFOLIO STANDARDS: OHIO

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EXECUTIVE SUMMARY

The U.S. has no federal mandate for "renewable" power production. Instead, a majority of states, including Ohio, have created their own state laws called Renewable Portfolio Standards (RPS). These laws mandate the presence of certain renewable sources among the overall menu of sources from which electricity companies produce power. This report analyzes how the changes in electricity markets caused by RPS alter the functioning of a state's economy and institutions, with a specific focus on Ohio. Our report uses a tax-based model, an empirical analysis, and a survey of legal rules. The following are our key findings:

- Our tax analysis found that Ohio's RPS will increase fiscal and economic costs significantly between now and 2026. During that period, Ohio electricity ratepayers will face $1.92 billion in elevated electricity costs beyond what they would have paid in the absence of an RPS. In addition, RPS will cause significant macroeconomic repercussions, including the loss of 3,590 jobs, a decrease in investment by $52 million, and a decrease in personal disposable income by $258 million in 2026 alone. To obtain these results, we used a mature, robust, computable general equilibrium (CGE) model, called STAMP (State Tax Analysis Modeling Program), developed by the Beacon Hill Institute at Suffolk University.
- Our empirical analysis suggests that the tax model is too modest. We discovered significant harmful effects on the economies of all states with RPS. States that have adopted an RPS have seen a drop in industrial electricity sales by almost 14 percent. Real personal income has fallen by almost four percent, which figures to a loss of $18 billion in 2013, or $3,842 less per family. Non-farm employment has declined by nearly three percent. Lastly, RPS is correlated with an increase of 10 percent in a state's unemployment rate, equaling a loss of 29,366 jobs in Ohio.
- Our analysis of the legal rules surrounding RPS in Ohio suggest that the regulatory climate is especially burdensome compared to most states we examined, making RPS an even worse venture for taxpayers than the tax-based or empirical analyses suggest.

BACKGROUND

Ohio's foray into renewable energy began in 1999, when the city of Bowling Green, along with nine other communities, began a wind energy project. Four years later, construction began in Bowling Green with the erection of two wind turbines, and two more followed in 2004. The four-turbine system could purportedly produce around seven megawatts of power, or about enough to power about 1,850 homes.[1] Today, the Bowling Green farm is one of several in the state.

In an effort to grow Ohio's renewable energy sector, Governor Ted Strickland included an RPS in his 2007 "Energy, Jobs, and Progress" plan. In response to the Governor's proposal to promote the use of renewable resources in Ohio, and restructure the regulatory system under which utility companies were then operating, legislators fashioned SB 221, which passed with near unanimous votes in both the state House and Senate.[2] Governor Strickland then signed the RPS bill into law in 2008, officially creating Ohio's Alternative Energy Portfolio Standard (AEPS).[3] In 2014, however, the Legislature passed SB 310, placing a freeze on required renewable energy ramp-ups and making Ohio the first state to scale back its RPS.[4]

When Ohio's AEPS first passed in 2008, it commanded utility companies to derive 25 percent of their energy from renewable resources by 2025. Half of that standard was to be met with "advanced" generating sources, i.e., "any new, retrofitted, refueled, or repowered generating facility located in Ohio," including fossil fuels, or any other sources that do not contribute extra carbon dioxide emissions to the atmosphere. The other half of the standard was to be met using

[1] Downing, B. (2010, January 10). Bowling Green wind farm might grow. *Akron Beacon Journal*. Retrieved from http://www.ohio.com/news/bowling-green-wind-farm-might-grow-1.161553. We note that capacity figures do not exactly reflect the actual amount of electricity sold to ratepayers, meaning such figures are inherently overoptimistic.

[2] Bricker & Eckler LLP. (2008). Ohio Senate Bill 221: A summary of its advanced energy and energy efficiency provisions. Retrieved from http://documents.lexology.com/23dba353-7d43-4e88-9db9-f414875607d5.pdf

[3] Ohio General Assembly. (n.d.a). Status Report of Legislation, 127th General Assembly, SB 221. Retrieved from http://lsc.state.oh.us/coderev/sen127.nsf/Senate+Bill+Number/0221?OpenDocument

[4] Ohio General Assembly. (n.d.b). Status Report of Legislation, 130th General Assembly, SB 310. Retrieved from http://lsc.state.oh.us/coderev/sen130.nsf/Senate+Bill+Number/0310?OpenDocument

renewables.[5] It also required utilities to implement energy efficiency and peak demand reduction programs. These programs had to achieve a cumulative energy savings of 22 percent by the end of 2025, and reduce peak demand by 1.0 percent in 2009 and 0.75 percent annually thereafter, through 2018.

Ohio legislators also included a list of qualifying renewable technologies as a part of the AEPS. Those technologies include solar thermal and photovoltaics, landfill gas, wind, biomass, hydroelectric, geothermal, municipal solid waste, CHP/cogeneration, waste heat, energy storage, clean coal, coal mine methane, advanced nuclear, anaerobic digestion, fuel cells using renewable fuels, and microturbines.[6]

SB 310 put a two-year freeze on the mandates, pushing the final benchmark year back to 2026. In addition, it removed in-state requirements for renewable energy procurement, meaning utilities could use as much electricity generated out of state as is needed to satisfy the AEPS.[7] During the two-year freeze, a committee will study the target goals of the RPS and make changes if they feel the requirements have been set too high. It is imperative that the committee and Legislature have access to sound information prior to further dialogue and decisions over Ohio's Renewable Portfolio Standards.[8]

There have been scarcely any examples of such controversies creating the requisite political pressure to repeal a law so quickly after first passage, but SB 310 is indicative of a climate conducive to such action. The bill is notable for a few reasons: Not only is it the first and only successful piece of legislation in the United States to scale back an already-existing RPS, but the timing with which it appeared is unprecedented, as it was passed just a few years after near unanimous acceptance of SB 221.[9] Such occurrences are rare opportunities to inform the

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[5] United States Department of Energy. (2014). Database of state incentives for renewables & efficiency. Retrieved from http://programs.dsireusa.org/system/program/detail/2934/
[6] *Ibid.*
[7] *Ibid.*
[8] Ohio General Assembly (n.d.b), *op. cit.*
[9] Gallucci, M. (2014, June 11). Ohio Gov. Kasich to sign "freeze" on state clean energy mandate by Saturday. *International Business Times.* Retrieved from http://www.ibtimes.com/ohio-gov-kasich-sign-freeze-state-clean-energy-mandate-saturday-1598602

public and decisions makers on the merits of RPS. The following sections of our report—detailing the results of our analyses—will be crucial toward that end.

RESULTS

TAX ANALYSIS WITH STAMP

Analysis Performed by the Beacon Hill Institute at Suffolk University

In light of the wide divergence in the cost estimates available for the different electricity generation technologies, we provide a statistically expected value—the quantitative effects that AEPS are expected to have on Ohio's economy—that will take place for the indicated economic variables. We measure the expected value against the counterfactual assumption that the AEPS mandate was not implemented. Appendix A explains the methodology. Table 1 displays the cost estimates and economic impact of the current 12.5-percent-by-2026 AEPS mandate.

TABLE 1: THE COST OF THE RPS MANDATE ON OHIO IN 2026

Costs Estimates (2012 $)	Expected Value
Total Net Cost in 2026	$281 million
Total Net Cost 2015-2026	$1,923 million
Electricity Price Increase in 2026 (cents per kWh)	0.20 cents
Percentage Increase (%)	1.86%
Economic Indicators	
Total Employment (jobs)	-3,590
Investment	-$52 million
Real Disposable Income	-$258 million

The current AEPS is expected to impose net costs of $281 million in 2026 alone, as a result of increasing electricity prices by an expected 0.20 cents per kilowatt-hour (kWh), or by 1.86 percent. We expect the AEPS mandate will cost Ohio's electricity customers $1.9 billion over the period from 2015 to 2026.

The STAMP model simulations indicate that, upon full implementation, the AEPS law is likely to hurt Ohio's economy. The state's ratepayers will likely face higher electricity prices that will increase their cost of living, which will in turn put downward pressure on households' disposable income. By 2026, the Buckeye State economy will shed 3,590 jobs in net. This includes jobs created in the renewable energy sector as well as the jobs lost due to higher electricity costs and dynamic spending decreases.

The job losses and price increases will reduce real incomes as firms, households and governments spend more of their budgets on electricity and less on other items, such as home goods and services. In 2026, real disposable income will fall by an expected $258 million, a per capita decrease by $22 in that year alone. Furthermore, net investment will fall by $52 million. Table 2 shows how the RPS mandate is expected to affect the average annual electricity bills of households and businesses in Ohio.

TABLE 2: ANNUAL EFFECTS OF THE RPS ON OHIO'S ELECTRICITY RATEPAYERS

Estimates (2012 $)	Expected Value
Cost in 2026	
Residential Ratepayer	$30
Commercial Ratepayer	$170
Industrial Ratepayer	$4,950
Cost over period (2015-2026)	
Residential Ratepayer	$190
Commercial Ratepayer	$1,165
Industrial Ratepayer	$32,915

In 2026, the RPS is expected to cost families an additional $30 per year; commercial businesses $170 per year; and industrial businesses $4,950 per year. Over the entire period from 2015 to 2026, the RPS will cost families an additional $190; commercial businesses $1,165; and industrial businesses $32,915.

SENSITIVITY ANALYSIS

We expand upon and support our initial results by undertaking a "Monte Carlo analysis," which gives a distribution of outcomes for each of the economic variables we considered. This gives a better sense of which outcomes are likely, rather than merely possible. It also measures the sensitivity of our results to the assumptions about the future values of the input variables.

For instance, in our initial analysis, we use the EIA estimates on levelized costs of energy (LCOE) of different electricity generation technologies through 2030. Changing circumstances, however, can cause the EIA estimates to change—examples being the steep drop in natural gas prices that took place over the past few years or, more recently, the decline in oil prices.

To compensate for such circumstances, we drew 10,000 random samples from the distributions, and computed the pertinent variables (rates of return, net present value, etc.). This allowed us to compute a distribution of outcomes, which shows the net present value of benefits minus costs, for the electricity price analysis. The full set of assumptions is detailed in Appendix A.

The most important feature of this risk analysis is that it allows us to compute confidence intervals for our target variables. These are shown in Table 3 below. Thus, we arrive at the 90 percent confidence interval for the net cost of electricity. In other words, we are 90 percent confident that the true result lies inside this band. The 90 percent confidence interval is a commonly accepted standard for making statistical inferences.[10] Thus, our conclusion, that the RPS mandate is economically harmful, is robust.

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[10] Anderson, D. R., Sweeney, D. J., & Williams, T. A. (2009). The essentials of statistics for business and economics (5th ed.) (pp. 298). Cincinnati, OH: Thomson South-Western Publishing.

TABLE 3: MONTE CARLO ANALYSIS (90-PERCENT CONFIDENCE INTERVAL) (CURRENCY IS MEASURED IN 2012 CONSTANT DOLLARS)

Changes in Electricity Costs (2012 dollars)	Best Case	Worst Case
Total Net Cost in 2026 ($ million)	-312	874
Total Net Cost 2015-2026 ($ million)	-2,289	6,136
Electricity Price Increase in 2026 (cents per kWh)	-0.22	0.62
Percentage Increase (%)	-2.06	5.77
Changes in Economic Indicators		
Total Employment (jobs)	3,990	-11,170
Investment ($ million)	58	-163
Real Disposable Income ($ million)	287	-802
Changes in Electricity Cost in 2026 (by sector)		
Residential Ratepayer	-30	85
Commercial Ratepayer	-190	535
Industrial Ratepayer	-5,505	15,410
Cost Over period (2015-2026)		
Residential Ratepayer	-230	610
Commercial Ratepayer	-1,390	3,725
Industrial Ratepayer	-39,235	105,065

The first row in Table 3 shows that with a 90 percent confidence, the net costs in 2026 will fall between a gain of $312 million and loss of $874 million, with the average between the two, a loss of $281, being our original expected outcome. These costs translate into average electricity price increases of 0.62 cents per kWh and decrease of 0.22 cents per kWh, or a 5.77 percent increase and 2.06 percent rate decrease. Thus, we are 90 percent confident that the outcome of the RPS mandate will fall within this range. The lower half of Table 3 translates these costs into increases in electric bills. Residential, commercial and industrial ratepayers would all see their bills increase, within our 90 percent confidence intervals.

For net employment changes, the analysis gives us a range from a gain of 3,990 jobs to a loss of 11,170 jobs; for disposable income the range is between a gain of $287 million and a loss of $802 million; and changes in net investment range from a $58-million gain and a $163-million loss. These are serious predictions, and while we should not take them for granted, our empirical analysis will grant us even greater confidence in our conclusions about the costs of RPS.

EMPIRICAL ANALYSIS

Analysis Performed by Tyler J. Brough, Ph.D., at Utah State University

STATE COINCIDENT EVENT STUDY

In this section, we present the results of an event study for state coincident indices—a methodology first fashioned by the Federal Reserve Bank of Philadelphia.[11] The event study indexes the economic conditions of all states across multiple points in time, and assigns as "point zero" each state's economic conditions on the dates of their respective RPS implementations. The study compares said economic conditions over a span from 48 months before to 48 months after that enactment date. The indices of each state RPS policy, therefore, while enacted in different calendar months and years, can thus be lined up in this so-called "event time," and the economic conditions in each state can be averaged. Given that RPS have been implemented in many states over a long period, this will minimize the effects of anomalies such as recessions and the enactment of other energy-related laws. For these reasons, the event study has become a time-honored empirical methodology in finance and economics and a standard course of analysis for the Philadelphia Fed. It is a simple but powerful method for measuring the effect of an exogenous shock to an economic variable of interest. MacKinlay gives an in-depth discussion of the event study methodology.[12] Table 4 presents the dates of 31 different states that have enacted an RPS policy.

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[11] Federal Reserve Bank of Philadelphia. (2015, January 29). State coincident indexes. Retrieved from http://www.philadelphiafed.org/research-and-data/regional-economy/indexes/coincident/

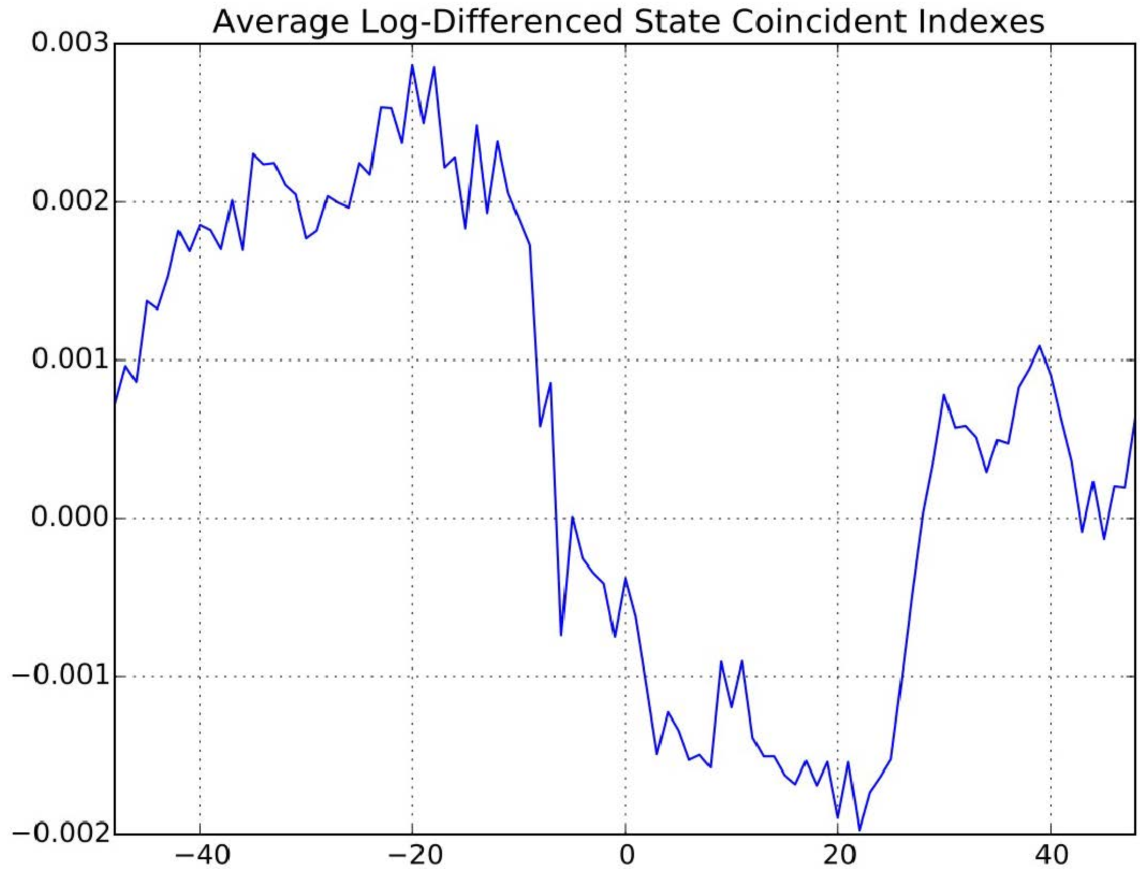
[12] MacKinlay, A.C. (1997). Event studies in economics and finance. *Journal of Economic Literature, 35*(1), 13-39.

TABLE 4: THE DATES (MONTH AND YEAR) OF THE 31 STATES THAT HAVE ENACTED AN RPS POLICY TO DATE

State	RPS Enactment Date
Arizona	July, 2007
California	January, 2003
Colorado	December, 2004
Connecticut	July, 1998
Delaware	July, 2005
Hawaii	December, 2003
Iowa	January, 1983
Illinois	August, 2007
Kansas	July, 2009
Massachusetts	April, 2002
Maryland	January, 2004
Maine	March, 2000
Michigan	October, 2008
Minnesota	February, 2007
Missouri	November, 2008
Montana	April, 2005
North Carolina	January, 2008
New Hampshire	July, 2007
New Jersey	September, 2001
New Mexico	September, 2007
Nevada	January, 1997
New York	September, 2004
Ohio	May, 2008
Oregon	January, 2007
Pennsylvania	February, 2005
Rhode Island	June, 2004
South Carolina	June, 2014
Texas	September, 1999
Washington	November, 2006
Wisconsin	December, 2001
West Virginia	July, 2009

The results of the event study are presented in Figure 1, wherein we see the response of the state coincident index to the enactment of RPS policies. The coincident index is a summary measure of the strength of a state economy, and is comprised of four economic indicators: nonfarm payroll employment, average hours worked in manufacturing, the unemployment rate, and wage and salary disbursements deflated by the Consumer Price Index (CPI).[13]

FIGURE 1: THE RESPONSE OF THE STATE COINCIDENT INDEX TO THE ENACTMENT OF RPS POLICIES.



The horizontal axis shows months before and after point zero (RPS enactment). The vertical axis shows an indexed scale measuring the average reaction of states in terms of several economic indicators.

As can be seen in Figure 1, the average effect on the state coincident index is a precipitous drop surrounding the enactment of an RPS policy. This evidence is suggestive of a negative effect of

[13] Federal Reserve Bank of Philadelphia. (2015, January 29). State Coincident Indexes. Retrieved from http://www.philadelphiafed.org/research-and-data/regional-economy/indexes/coincident/

an RPS policy on a state economy. While suggestive, the evidence from the event study warrants further exploration into the effects, since state economies also appear to decline several months prior to the enactment of an RPS. The next section presents the structural panel VAR-X model, which provides further evidence of the negative economic effects of an RPS.

THE STRUCTURAL PANEL VAR-X MODEL

The VAR model takes into account the nature of the state macroeconomic variables that could provide unwanted feedback into the model, and considers their dynamic interactions. By including a panel dimension to the model we can include the data for multiple states in a single model. We include fixed effects to control for state-level heterogeneity. We impose a recursive causal ordering on the VAR-X model to allow for structural interpretation of dynamic multiplier analysis of the RPS policy variable. Table 4 presents the cumulative effects of an RPS on the state economy via structural policy simulations.

TABLE 5: THE LONG-RUN EFFECTS ON STATE MACROECONOMIC VARIABLES

State Economic Variable	**Long-Run Effect**
Electricity Sales	-13.7075%
Real Personal Income	-3.6369%
Non-farm Employment	-2.8416%
Manufacturing Employment	3.7454%
Unemployment Rate	9.6841%

The cumulative effect of the enactment of an RPS policy on state electricity sales is a staggering 13.7-percent decline. This is, perhaps, not surprising as the RPS increases the cost of electricity generation. Real personal income declines in the long run by 3.6369 percent, which figures to a loss of $18 billion in 2013, or $3,842 less per family.[14] Non-farm employment declines in the long run by 2.8 percent. Only one analyzed component of non-farm employment, manufacturing employment, does not experience a long-term suppression in response to an RPS policy, although as we see in the later graphical analysis, it does still experience a sharp decline in the short term. Most significantly, the state unemployment rate increases by 9.6 percent. This means that, at the end of last year, Ohio had 29,366 fewer jobs than it would have had without the RPS.[15] There can be no doubt that the combined economic effect on an RPS enactment, as measured by the structural panel VAR-X model, is a severe decline in the Ohio economy. A graphical representation of the analysis, showing the changes over time that lead to these results, can be found in Appendix C.

CONCLUSIONS FROM THE EMPIRICAL ANALYSIS

We demonstrate strong empirical evidence that a Renewable Portfolio Standard has a lasting negative effect on a state economy. We present this evidence from both an event study of the state coincident index as measured by the Federal Reserve Bank of Philadelphia, as well as from structural policy simulations from a panel VAR-X model. The long-run effect of an RPS on state industrial production, as measured by electricity sales, is greater than a 13-percent decline. Real personal income declines in the long run after an RPS by almost 4 percent. The cumulative effect of an RPS on non-farm employment is nearly 3 percent. While the effect of an RPS on manufacturing employment is not as severe in the long run, it too demonstrates an initial sharp decline lasting for several years. Finally, the state unemployment rate increases in the long run in response to an RPS by nearly 10 percent. These are strong and lasting effects in 4 of the 5 variables measuring the state economy. The combined econometric evidence makes clear that an RPS policy has a severely negative economic effect on a state that enacts such.

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[14] Bureau of Economic Analysis. (n.d.). Regional Data, Annual State Personal Income and Employment. Retrieved from http://www.bea.gov/iTable/iTable.cfm?reqid=70&step=1&isuri=1&acrdn=1#reqid=70&step=1&isuri=1

[15] Bureau of Labor Statistics (n.d.). Ohio. Retrieved from http://www.bls.gov/regions/midwest/ohio.htm

INSTITUTIONAL ANALYSIS

Our survey of the legal rules surrounding the AEPS provides a detailed account of all the regulations that hinder the state, generators, and utilities in achieving compliance. This "institutional analysis" reveals a number of factors that add arduousness to the process of complying with the requirement that electric utilities supply 25 percent of their retail electricity sales through renewable and advanced energy sources by 2026.

The Public Utilities Commission of Ohio (PUCO) uses Renewable Energy Certificates (RECs) to track utility compliance. One REC represents exactly one megawatt-hour (MWh) of electricity generated from a qualifying source, and has a lifetime of five years from the date the utility acquires it.[16]

A utility's renewable electricity obligation is equal to the AEPS' statutory requirement as applied to the preceding three-year average of a utility's total retail sales.[17] States with restructured electricity markets, i.e., where utilities trade RECs on one or more exchanges, generally follow this model, basing renewable electricity obligations on total retail sales—an alternative method being to base the obligation on total generating capacity, as is the case in Kansas—but there are some notable drawbacks with this.[18] Many utilities have expressed reservations about the historical sales volume model, which, "given customer migration, may require companies to 'over-comply' relative to current sales base […]"[19] Compensating for this risk would cause an overly large corrective reaction that ultimately slows compliance, but the equally undesirable alternative is to invest more than is necessary, translating into higher-than-necessary economic costs. At the very least, this creates uncertainty in the market, which

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[16] Public Utilities Commission of Ohio. (2010, January 22). Ohio Administrative Code, Chapter 4901:1-40. Retrieved from http://codes.ohio.gov/oac/4901%3A1-40
[17] *Ibid.*
[18] National Renewable Energy Laboratory. (2014, May). A survey of state-level cost and benefit estimates of Renewable Portfolio Standards. J. Heeter, G. Barbose, L. Bird, S. Weaver, F. Flores-Espino, K. Kuskova-Burns, & R. Wiser. Retrieved from http://www.nrel.gov/docs/fy14osti/61042.pdf
[19] Public Utilities Commission of Ohio. (2014). DRAFT Alternative Energy Portfolio Standard Report. Retrieved from http://dis.puc.state.oh.us/TiffToPDf/A1001001A14A14B02242C15874.pdf, p.29

"creates some unwillingness by companies [utilities] to enter longer-term contracts."[20] Renewable electricity generators, on the other hand, have a strong affinity for such contracts, which are integral in securing the capital investment required to build generation facilities.

The AEPS originally required utilities to meet half of their total obligations using electricity provided by facilities within Ohio, but that requirement was dropped in 2014 via SB 310, largely due to the fact that average costs for out-of-state RECs were significantly lower than for in-state RECs.[21] The underlying reason for that cost disparity—the limited supply of in-state RECs, especially solar RECs—was a concern that several Ohio utilities have expressed in their annual mandated compliance reports.[22] Although SB 310 addressed this problem, the old requirement likely contributed to utilities' solar sluggishness in the early years of the program. In 2009, utilities retired enough RECs to satisfy only 22 percent of the in-state solar requirement.[23]

The in-state generation bias was not the only self-defeating aspect of the AEPS, however. Only facilities with a placed-in-service date of January 1, 1998 or later qualify to meet the standard, excluding many older, yet working, renewable or advanced electricity generating facilities.[24]

Even forgetting the aforementioned concerns, the process of gaining approval to generate RECs is not as painless as the regulatory verbiage suggests. First, in order to qualify their alternative generation facilities under the law and generate RECs, electricity generators must submit an application to PUCO.[25] The application is operated on a 60-day auto approval process,[26] although human error and applications asking for permission to generate from new, unfamiliar, alternative technologies not covered by the law will cause appreciable delays in the

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[20] *Ibid.*
[21] *Ibid.*
Ohio Legislative Service Commission. (n.d.). Am. Sub. S.B. 310. Retrieved from http://www.lsc.ohio.gov/analyses130/s0310-ps-130.pdf
[22] Public Utilities Commission of Ohio. (2014). DRAFT Alternative Energy Portfolio Standard Report. Retrieved from http://dis.puc.state.oh.us/TiffToPDf/A1001001A14A14B02242C15874.pdf, p. 29
[23] Public Utilities Commission of Ohio. (2012, August 15). Alternative Energy Portfolio Standard Report by the Public Utilities Commission to the General Assembly of the State of Ohio for Compliance Years 2009 and 2010. Retrieved from http://dis.puc.state.oh.us/TiffToPDf/A1001001A12H15B51144H86168.pdf
[24] United States Department of Energy (2014), *op. cit.*
[25] Public Utilities Commission of Ohio (2010, January 22), *op. cit.*
[26] *Ibid.*

approval process. Once approved, generators must then register their generated RECs with a tracking system, typically PJM Interconnection's Generation Attribute Tracking System (PJM-GATS). Only once generation facilities have been registered can generators make their RECs available for buying/selling or retirement for meeting the annual benchmarks.[27]

Utilities that fail to meet the renewable energy benchmarks must make an Alternative Compliance Payment (ACP) to the Ohio Advanced Energy Fund, which is used to fund renewable energy and energy efficiency projects.[28] The amount due for an ACP differs depending on the type of generation source for which a utility lacks renewable electricity certificates, and the Commission updates these amounts annually. For solar RECs, the amount of the ACP is reduced by $50 every two years through 2026, to a minimum of $50. For example, in the years of 2014 through 2016, lacking a sufficient number of solar RECs results in a $300 fine per MWh deficient; for the years 2017 through 2018, and years 2019 through 2020, these ACPs will cost $250 and $200 respectively. On the other hand, failure to meet the *non-solar* renewable energy benchmark in 2009 resulted in a fine of only $45 per MWh deficient, and in 2014 the fine was $49.22 per MWh deficient. PUCO increases the non-solar ACP amounts in accordance with the Consumer Price Index.[29]

There are two ways utilities can exempt themselves from AEPS' requirements, but even these processes carry inherent problems. For example, utilities are exempt from the obligation to meet annual benchmarks if the cost of compliance raises costs by three percent or more above what they would have been otherwise.[30] The burden of proof in claiming that costs will exceed the cap, however, rests solely on the utility, which encumbers it with further administrative burdens.[31] Alternatively, in the event that a utility is unable to meet its annual benchmark, it may apply for a force majeure determination, temporarily excluding the utility from its requirements

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[27] *Ibid.*
[28] *Ibid.*
[29] United States Department of Energy (2014), *op. cit.*
[30] Public Utilities Commission of Ohio (2010, January 22), *op. cit.*
[31] *Ibid.*

due to unforeseen economic circumstances and constraints. This process can take up to 90 days.[32]

During the force majeure determination process, utilities will be uncertain as to their liability—not only for the preceding year, but for the following year, since the Commission "retains the right to increase a future year's compliance obligation by the amount of any under compliance in a previous year that is attributed to a force majeure determination."[33] This can make decisions to invest alternative energy technologies both tenuous and perilous. In addition, the imposition of costs caps can, as discussed in previous reports, effectively neuter the prospects of compliance, since recovering the costs of compliance from ratepayers is a necessary action in meeting RPS benchmarks.[34,35]

As mentioned previously, utilities are also required to take measures to increase energy efficiency. The AEPS mandates that utilities reduce peak energy demand by one percent in 2009 and an additional 0.75 percent every year through 2018.[36] Additionally, utilities are required to achieve energy savings of 22 percent by 2025 through energy efficiency programs.[37] Consumption-side generation practices, such as net metering, can be used toward this end. For example, a qualified utility customer with a rooftop solar array will receive a credit for any generated electricity that is added to the grid. Homeowners must hassle themselves with the same application process as the larger generators, however; and net metering, specifically, presents its own set of problems in terms of trans-customer cost-shifting and grid reliability.

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[32] *Ibid.*
[33] *Ibid.*
[34] Climate Policy Initiative. (2012, December). Renewable portfolio standards – the high cost of insuring against high costs. San Francisco: Brendan Pierpont. Retrieved from http://climatepolicyinitiative.org/2012/12/17/renewable-portfolio-standards-the-high-cost-of-insuring-against-high-costs/
[35] Simmons, R. T., Yonk, R. M., Brough, T., Sim, K., Fishbeck, J. (2015, February). Renewable Portfolio Standards: North Carolina. *Institute of Political Economy, Utah State University.* Retrieved from http://www.strata.org/wp-content/uploads/2015/03/FINAL-RPS-North-Carolina.pdf
[36] United States Department of Energy. (2014), *op. cit.*
[37] *Ibid.*

CONCLUSIONS FROM THE INSTITUTIONAL ANALYSIS

Even in judging the AEPS on its own terms, and assuming that all potential economic ramifications are acceptable, the legal and regulatory structure behind the AEPS makes compliance itself a difficult task; this fact does not change even in spite of the good-faith efforts made by utilities. Proponents of RPS often gloss over these considerations and assume that the mere presence of a law is solely required to effect their desired outcome. Our analysis clearly demonstrates that reality is more complicated.

CONCLUSION

The evidence from these studies paints a clear picture about the effects of RPS. Our tax analysis with STAMP found that Ohio's RPS will increase fiscal and economic costs significantly between now and 2026. These costs include a $1.92-billion burden on Ohio ratepayers, a loss of 3,590 jobs, a decrease in investment by $52 million, and a decrease in personal disposable income of $258 million in 2026 alone. Our empirical analysis more than corroborates these projections, finding a drop in industrial electricity sales by almost 14 percent, real personal income by almost four percent, non-farm employment by nearly three percent and an increase of 10 percent in the unemployment rate, which for Ohio equals a loss of 29,366 jobs. Our analysis of the legal rules surrounding Ohio's AEPS describes the barriers that make it difficult for utilities to comply and for bureaucracies to enforce it, finding that Ohio's excessive bureaucracy and cost caps hinder compliance by creating uncertainty and erecting political barriers to reaching the mandates. Any state currently deliberating on implementing a new RPS, or strengthening an existing one, should heed these results as a warning of their harmful effects. Finally, states should refrain from following the fad of enacting such costly regulations, in spite of the policy's political palpability or expediency.

APPENDIX A

TECHNICAL CONSIDERATIONS OF THE BEACON HILL INSTITUTE'S STUDY IN OHIO

Authored by the Beacon Hill Institute at Suffolk University

To provide a statistically significant confidence interval for net cost calculations for the Ohio state level Alternative Energy Portfolio Standards (AEPS), we used a Monte Carlo simulation. A Monte Carlo simulation is generated by repeated random sampling from a distribution to obtain statistically significant results. This allows for the determination of the range and probability of the cost and percent change outcomes of a policy based on distributions placed on key, specific variables, as discussed in this appendix. Oracle's Crystal Ball software provided an easy-to-use and established methodology for generating the results.[38]

The following methodology was used to calculate the underlying numbers that went into the Ohio AEPS calculation.

DETERMINING THE LEVELIZED ENERGY COST DISTRIBUTION

Determining the mean value and standard deviation of electricity costs is the first step in building a Monte Carlo simulation. We relied upon data from the U.S. Energy Information Administration's (EIA) Annual Energy Outlook (AEO) Levelized Energy Costs (LEC). The 2014 AEO explains:

> Levelized cost of electricity (LCOE) is often cited as a convenient summary measure of the overall competiveness of different generating technologies. It represents the per-kilowatt hour cost (in real dollars) of building and operating a

[38] Oracle Crystal Ball, *op. cit*.

> generating plant over an assumed financial life and duty cycle. Key inputs to calculating LCOE include capital costs, fuel costs, fixed and variable operations and maintenance (O&M) costs, financing costs, and an assumed utilization rate for each plant type.[39]

Using this comprehensive and widely accepted methodology, we utilized the detailed regional data set from the 2013 AEO, allowing us to go into extensive depth. We defined LEC for every year between 2014 and 2030, across 22 different regions for 17 different types of electricity generating technologies. For example, the mean cost to produce a megawatt-hour (MWh) of power from wind power in the Northeast Power Coordinating Council/New England region for a plant coming online in 2020 was calculated and represented as Mean(Wind, NPCC/NE, 2020). This level of detail enabled the modeling of state specific RPS with varying requirements year to year.

Two different data sets were examined to calculate the variables required for the Monte Carlo simulation. The first was the LEC as modeled by the National Energy Modeling System from the AEO2008. The second was the 'No Sunset' version of the same data set from the AEO2013. The No Sunset version was preferable for our analysis because it assumes that expiring tax credits would be extended, which we believe is the most likely scenario.[40] Additionally, since the vast majority of expiring tax credits are for renewable generation sources, such as wind, solar and biomass, it makes the projections much more conservative.

Before calculating the mean and standard deviation for each data point, some minor adjustments to the AEO2008 data were required to match with the AEO2013 data. The first step was to grow the AEO2008 numbers, originally in 2006 US dollars, so that they were in 2011 US dollars like the AEO2013 data. To do this, the annual U.S. Consumer Price Index for Energy was employed. The index was at 196.9 in 2006 and 243.909 in 2011, resulting in the AEO2008 prices being multiplied by approximately 1.24.[41] Additionally, the 13 regions from AEO2008 had to be

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[39] U.S. Energy Information Administration, (2015, January 1), *op. cit.*
[40] Energy Information Administration (2013, April), *op. cit.*
[41] U.S. Bureau of Labor Statistics. (n.d.), *op. cit.*

matched up with the 22 regions of AEO2013. For some this was a simple conversion, such as the Florida Reliability Coordinating Council from AEO2008, which did not change in the AEO2013. But others were split up into 2 or 3 different regions, for example region 1 in the AEO2008 was split up such that it became region 10, 11 and half of 15 (the other half of 15 came from region 9 in AOE2008). Table 4 below shows our matching.

TABLE 4: AEO2008 TO AOE2013 REGION MATCHING

AEO 2008 Region*	AEO 2013 Region*
1	10, 11, (½)15,
2	1
3	6, 7, 9
4	3, (⅓) 4, 13
5	(⅔)4
6	8
7	5
8	2
9	12, 14, (½)15, 16
10	17, 18
11	21
12	19, 22
13	20

* Numbers based on Electricity Market Module Regions from the respective AEOs.

With the data in the same year and regions, we compared the TOTAL from AEO2008 to the TOTAL from AEO2013. The AEO2013 added in additional information in the form of ITC/PTC, which stands for 'Investment Tax Credit/Production Tax Credit'—a negative cost to the producer of the energy. This was added back into the calculations after, as it did not exist in the AEO2008, allowing an 'apples-to-apples' comparison. We calculated the mean for each of these data points. This was accomplished by comparing the projections of LEC from the AEO2008 to those made in the AEO2013.[42][43] This represents what we believe best corresponds to the expected value around which a normal distribution of possible outcomes is centered.

To calculate each individual standard deviation – for example, Standard Deviation (Wind, 5, 2020) – we calculated the sample standard deviation between the AEO2008 and

[42] Energy Information Administration, (2008), *op. cit.*
[43] Energy Information Administration, (2014, May 7a), *op. cit.*

AEO2013 points. With these two calculations completed, the result allowed us to create projections of normal distributions for the LEC of various energy production techniques.

The only exception to this method was for solar photovoltaic production. The change in forecasted prices from AEO2008 to AEO2013 was very large, mainly due to assumptions made at the time. During the forecasting of the AEO2008, raw material prices, including rare earth metals, were at or near all-time highs. During the AEO2013, solar companies were going out of business as government incentives, competition from China and increased investment in raw material mining drove down the costs of solar. For this reason, we set the standard deviation equal to one quarter of the distance between the two projections. In essence this means that 95 percent of the selections by Crystal Ball will fall between the two projections.

ADDITIONAL DATA

With the distributions of LEC we next utilized the Public Utilities Commission of Ohio's projections of sales subject to the RPS through 2025.[44] For year 2026, we calculated the average annual increase in their projections between 2012 and 2025 and used it to generate the 2026 number. To these annual sales we applied the annual increases in both the overall state RPS and the Solar carve out, from 2015 till 2026, resulting in the amount of solar, and other renewables annually required. With electricity consumption defined, we looked to other data points that required estimates – the first of which was baseline sales of renewable energy.

The level of renewable generation that would have come online without taking into consideration the policy under review would not be attributed to the RPS policy. The difference between this baseline and the policy requirement is the amount of renewable energy that has to come online due to the policy itself. The baseline level of renewables was set equal to the total amount of renewable generation in at the start of 2008, as the policy was introduced in SB 221 in

[44] Ohio Public Utilities Commission. (2014, October 16). *Estimated quantification of statewide compliance obligations associated with Renewable Portfolio Standard.* Retrieved from http://www.puco.ohio.gov/puco/assets/File/RPS%20Estimate%20for%20PUCO%20Website%20with%20SB310%20%28V4_0%29.pdf

mid-2008.[45] This amount was then grown annually according to the projected growth of renewables in the region per the AEO2007.[46][47]

The second data point calculated was the distribution of new renewable production that came online due to the policy. The share of new renewable generation was calculated based on several data points. Firstly, electricity demanded times the solar carve out minus baseline solar energy that would have come online resulted in total solar required due to the RPS law. Secondly the electricity demanded times the RPS level, minus solar carve out, minus baseline resulted in the additional other forms of renewable energy that would have to come online due to the RPS law. This amount was attributed to the various eligible renewable energies based on annual reports from the Public Utilities Commission of Ohio.[48]

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[45] Energy Information Administration. (2014, May 1c). Ohio electricity profile 2012, table 5: Electric power industry generation by primary energy source, 1990-2012. Retrieved from http://www.eia.gov/electricity/state/ohio/

[46] Energy Information Administration. (2007, February). Supplemental tables to the Annual Energy Outlook, table 62: Electric power projections for EMM region. Retrieved from http://www.eia.gov/forecasts/archive/aeo07/supplement/pdf/sup_elec.pdf

[47] *Ibid.*, table 78: Renewable energy generation by fuel.

[48] Public Utilities Commission of Ohio. (2014, January 14). DRAFT Alternative Energy Portfolio Standard report by the staff of the Public Utilities PUCO of Ohio for the 2012 compliance year, Chart 1 through Chart 7. Retrieved from http://dis.puc.state.oh.us/TiffToPDf/A1001001A14A14B02242C15874.pdf

TABLE 5: PROJECTED ELECTRICITY SALES, RENEWABLE SALES

Year	Projected Electricity Sales MWhs (000s)	Projected Renewable MWhs (000s)	RPS Requirement MWhs (000s)
2015	136,780	398	3,420
2016	137,805	398	3,445
2017	138,827	404	4,859
2018	139,845	407	6,293
2019	138,444	403	7,614
2020	137,034	399	8,907
2021	135,617	396	10,171
2022	136,648	399	11,615
2023	137,674	408	13,079
2024	138,697	413	14,563
2025	139,715	414	16,067
2026	140,109	414	17,514

Some types of renewable generation, such as wind and solar power, are considered intermittent power sources.[49] That is, output varies greatly over time, depending on numerous difficult-to-predict factors. If the wind blows too slowly, too fast, or a cloud passes over a solar array, the output supplied changes minute to minute while demand will not mirror these changes. For this reason, conventional types of energy are required as 'spinning reserves.' That is, they need to be able to ramp up — or down—output at a moment's notice. The effect of this is that for every one MWh of intermittent renewable power introduced, the offset is not one MWh of conventional power, but some amount less. To account for this, we used a policy study from the Reason Foundation that noted:

> Gross et al. show that the approximate range of additional reserve requirements is 0.1 percent of total grid capacity for each percent

[49] Narbel, P. A., *op. cit.*

> of wind penetration for wind penetrations below 20 percent, rising to 0.3 percent of total grid capacity for each percent of wind penetration above 20 percent.[50]

We reviewed the original Gross article, which compiled numerous papers on the topic, and found the Reason Foundation calculations to be very conservative. Using the Reason Foundation numbers to err on the modest side, (i.e. factoring in less spinning reserves), the results from this calculation were more favorable to renewable sources.

Finally, a calculation of the distribution of conventional energy resources is needed – one that finds out how much would be crowded out due to a higher share of renewables. In Ohio, coal and natural gas are the most likely sources of conventional energy to be replaced. Nuclear power is not expected to be replaced because it is a baseline source of power that is unlikely to be replaced. Natural gas and coal make up a majority of the remaining non-RPS sources and are more dispatchable and therefore likely to be the generation techniques replaced.[51] For this reason, we assume that approximately 87 percent of the replaced electricity sources will be coal, and the remainder natural gas, depending on the ratio of the projected energy source by year.

Using the above-compiled data, we were able to calculate the amount of new renewables that will likely come online due to the policy, as well as the likely conventional energy displaced. Combining this information with the estimated LEC of electricity in each of the studied years yields the total cost of the policy. The total cost of the policy divided by the amount of electricity consumed yields a percent cost of the policy.

RATEPAYER EFFECTS

To calculate the effect of the policy on electricity ratepayers, we used EIA data on the average monthly electricity consumption by type of customer: residential, commercial and

[50] Korchinski, W. J., & Morris, J., *op. cit.*
[51] U.S. Energy Information Administration, (2014, May 1c), *op. cit.*

industrial.[52] The monthly figures were multiplied by 12 to compute an annual figure. We inflated the 2012 figures for each year using the regional EIA projections of electricity sales.[53]

We calculated an annual per-kWh increase in electricity cost by dividing the total cost increase — calculated in the section above — by the total electricity sales for each year. We multiplied the per-kWh increase in electricity costs by the annual kWh consumption for each type of ratepayer for each year. For example, we expect the average residential ratepayer to consume 10,604 kWh of electricity in 2026 and the expected percent rise in electricity is 1.856 percent of the baseline residential electricity price of 14.159 cents per kWh in the same year. Therefore, we expect residential ratepayers to pay an additional $28 in 2026.

MODELING THE POLICY USING STAMP

We simulated these changes in the STAMP model as a percentage price increase on electricity to measure the dynamic effects on the state economy. The model provides estimates of the proposal's impact on employment, wages and income. Each estimate represents the change that would take place in the indicated variable against a "baseline" assumption of the value that variable for a specified year in the absence of the RPS policy.

Because the policy requires households and firms to use more expensive renewable power than they otherwise would have under a baseline scenario, the cost of goods and services will increase under the policy. These costs would typically manifest through higher utility bills for all sectors of the economy. For this reason, we selected the sales tax as the most fitting way to assess the impact of the policy. Standard economic theory shows that a price increase of a good or service leads to a decrease in overall consumption, and consequently a decrease in the production of that good or service. As producer output falls, the decrease in production results in a lower demand for capital and labor.

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[52] Energy Information Administration, (2013, November 8), *op. cit.*

[53] Energy Information Administration. (2014, May 7d). Annual Energy Outlook 2014. table 83: Electric power projections by electricity market module region. Retrieved from http://www.eia.gov/forecasts/aeo/tables_ref.cfm

The STAMP® model identifies the economic effects and understand how they operate through a state's economy. STAMP is a five-year dynamic CGE (computable general equilibrium) model that has been programmed to simulate changes in taxes, costs (general and sector-specific) and other economic inputs. As such, it provides a mathematical description of the economic relationships among producers, households, governments and the rest of the world. It is general in the sense that it takes all the important markets, such as the capital and labor markets, and flows into account. It is an equilibrium model because it assumes that demand equals supply in every market (goods and services, labor and capital). This equilibrium is achieved by allowing prices to adjust within the model. It is computable because it can be used to generate numeric solutions to concrete policy and tax changes.[54]

In order to estimate the economic effects of the policy we used a compilation of six STAMP models to garner the average effects across various state economies: New York, Pennsylvania North Carolina, Indiana, Kansas, and Washington. These models represent a wide variety in terms of geographic dispersion (Northeast, Southeast, Midwest, the Plains and West), economic structure (industrial, high-tech, service and agricultural), and electricity sector makeup.

Using three different utility price increases – 1 percent, 4.5 percent and 5.25 percent – we simulated each of the six STAMP models to determine what outcome these utility price increases would have on each of the six states' economy. We then averaged the percent changes together to determine the average effect of the three utility increases. Table 6 displays these elasticities, which were then applied to the calculated percent change in electricity costs for the state as discussed above.

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[54] For a clear introduction to CGE tax models, see Shoven, J. B., & Whalley, J., (1984, September). Applied general-equilibrium models of taxation and international trade: An introduction and survey. *Journal of Economic Literature 22*(1008). Shoven and Whalley have also written a useful book on the practice of CGE modeling entitled *Applying General Equilibrium* (Cambridge: Cambridge University Press, 1992).

TABLE 6: ELASTICITIES FOR THE ECONOMIC VARIABLES

Economic Variable	**Elasticity**
Employment	-0.022
Investment	-0.018
Disposable Income	-0.022

We applied the elasticities to percentage increase in electricity price and then applied the result to state level economic variables to determine the effect of the policy. These variables were gathered from the Bureau of Economic Analysis Regional and National Economic Accounts as well as the Bureau of Labor Statistics Current Employment Statistics.[55]

[55] For employment, see the following: U.S. Bureau of Labor Statistics. (n.d.). State and metro area employment, hours, & earnings. Retrieved from http://bls.gov/sae/. Private, government and total payroll employment figures for Michigan were used. For investment, see U.S. Bureau of Economic Analysis. (n.d.). National income and product account tables. Retrieved from http://www.bea.gov/itable/. See also BEA. (n.d.). Gross domestic product by state. Retrieved from http://www.bea.gov/regional/. We took the state's share of national GDP as a proxy to estimate investment at the state level. For state disposable personal income, see BEA. (n.d.). State disposable personal income summary. Retrieved from http://www.bea.gov/regional/.

APPENDIX B

EXPLANATION OF EMPIRICAL STUDY METHODOLOGY

Methodology Constructed by Tyler Brough, Ph.D.

In this technical appendix, we outline the details of the structural panel VAR-X model, its estimation, and its use for policy simulation.

0.1. The Panel VAR-X Model

The vector autoregressive (VAR) model is the standard work horse model in empirical macroeconomics. The basic p-lag VAR model can be written as:

$$y_t = a_0 + \sum_{j=1}^{p} A_j\, y_{t-j} + \varepsilon_t$$

where y_t for t = 1, . . . , T is an M vector of observations on M time series variables, ε_t is an $M \times 1$ vector of errors, a_0 is an $M \times 1$ vector of intercepts and the A_j are $M \times M$ matrices containing model coefficients.[56] This is the reduced-form VAR model. For the present study $y_t = (y_{1t},...,y_{Mt})'$, M = 5, and the y_{jt} are the five state macroeconomic variables presented in the main body of the paper, namely electricity sales, real personal income, non-farm employment, manufacturing employment, and the unemployment rate. Thus, the VAR model is a system of M equations, with one equation for each variable in the system. Each of the M = 5 variables is treated as endogenously determined.

The present model also includes an exogenous policy variable that represents the enactment of an RPS by a given state. Thus, we can now write the VAR-X (a VAR model with the exogenously determined variable) as follows:

$$y_t = a_0 + \sum_{j=1}^{p} A_j\, y_{t-j} + \sum_{k=1}^{q} B_{t-k}\, X_{t-k} + \varepsilon_t$$

[56] Lutkepohl, H. (2005, Spring). *New introduction to multiple time series analysis*, Chapter 2.

where the X_{t-k} vectors contain the exogenous variables and their lags, and the B matrices contain the coefficients respectively. The variables in the X vector affect the state of the other variables, but are not themselves determined by the system of equations, and thus are considered exogenous.

In addition, the present model adds a cross-sectional dimension to the basic VAR(p) model by essentially stacking the VAR models for the different states on top of each other. In other words, the panel VAR-X model is:

$$y_{1,t} = a_{1,0} + \sum_{j=1}^{p} A_j\, y_{1,t-j} + \sum_{k=1}^{q} B_{t-k}\, X_{t-k} + \varepsilon_{1,t}$$

$$\vdots$$

$$y_{M,t} = a_{M,0} + \sum_{j=1}^{p} A_j y_{M,t-j} + \sum_{k=1}^{q} B_{t-k}\, X_{t-k} + \varepsilon M, t$$

See Canova and Ciccarelli for an excellent survey of panel VAR methods.[57] One thing of note is that in the present study we do not focus on estimating dynamic heterogeneities between the different state economies as is done in many panel VAR models for large macroeconomic studies. Instead we focus on the average effect of an RPS enactment on a state economy. To that end, we estimate the model with fixed effects to control for possible heterogeneities across states.[58] It is possible to recover the state fixed effects, though we make no effort to do so here as the focus of the study is on the average effect of an RPS and not on individual state effects.

0.2. Model Estimation

We use Bayesian techniques, namely the Gibbs sampler, to estimate the structural panel VAR-X model. See Ciccarelli and Rebucci for a review of Bayesian methods for VAR models.[59] See also

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[57] Canova, F., & Ciccarelli, M. (2013). Panel vector autoregressive models: A survey.
[58] Greene, William. (2012). *Econometric Analysis*. Upper Saddle River, NJ: Prentice Hall.
[59] Ciccarelli, M., & Rebucci, A. (2003). Bayesian VARs: A survey of recent literature with an application to the European monetary system.

Ocampo and Rodr´ıguez for a very practical tutorial.[60] We follow their Algorithm 3 for Bayesian estimation, which for simplicity we reproduce below.

Algorithm 1 Bayesian Estimation

1. Select the specification for the reduced form VAR-X, that is to choose values of p (endogenous variables lags) and q (exogenous variables lags) such that the residuals of the VAR-X (ε) have white noise properties. With this the following variables are obtained: T, p, q, k, where:

$$k = 1 + np + m(q + 1)$$

2. Calculate the values of $\hat{\Gamma}$, S with the data (Y , Z) as:

$$\hat{\Gamma} = (Z'Z)^{-1}Z'Y \qquad\qquad S = (Y - Z\hat{\Gamma})'(Y - Z\hat{\Gamma})$$

3. Generate a draw for matrix Σ from an inverse Wishart distribution with parameter S and $T - k$ degrees of freedom.

$$\Sigma \sim iW_{pdf}(S, T - k)$$

4. Generate a draw for matrix Γ from a multivariate normal distribution with mean $\hat{\Gamma}$ and covariance matrix $\Sigma \otimes (Z'Z)^{-1}$

$$\Gamma | \Sigma \sim MN_{pdf}(\hat{\Gamma}, \Sigma \otimes (Z'Z)^{-1})$$

5. Repeat steps 2-3 as many times as desired, save the values of each draw.

The draws generated can be used to compute moments of the parameters. For every draw the corresponding structural parameters, impulse response functions, etc. can be computed, then their moments and statistics can also be computed. The algorithm for generating draws for the inverse Wishart and multivariate normal distributions are presented in Bauwens et al., Appendix B.[61]

Observe that in this notation:

[60] Ocampo, S., & Rodríguez, N. (2012). An introductory review of a structural VAR-X estimation and applications. *Revista Colombiana de Estadística, 3*, 479-508.

[61] Bauwens, L., Lubrano, M., & Jean-Francois, R. (2000). *Bayesian inference in dynamic econometric models.* Oxford, UK: Oxford University Press.

$$Y = \begin{bmatrix} y'_1 \\ \vdots \\ y'_t \\ \vdots \\ y'_T \end{bmatrix}$$

,

$$Z = \begin{bmatrix} 1 & y'_0 & \cdots & y'_{1-p} & x'_1 \\ \vdots & & & & \\ 1 & y'_{t-1} & \cdots & y'_{t-p} & x'_t \\ \vdots & & & & \\ 1 & y'_{T-1} & \cdots & y'_{T-p} & x'_T \end{bmatrix}$$

,

$$E = \begin{bmatrix} \varepsilon'_1 \\ \vdots \\ \varepsilon'_t \\ \vdots \\ \varepsilon'_T \end{bmatrix}$$

and finally,

$$\Gamma = \begin{bmatrix} v & A_1 & \ldots & A_p & B_0 & \cdots & B_q \end{bmatrix}$$

Then the VAR-X model can be written simple as

$$Y = Z\Gamma + E$$

We set $p = 3$ and $q = 1$ for simplicity.

0.3. Dynamic Multiplier Analysis

During the Gibbs sampling simulation, which we run for 5, 000 replications with 500 burn-in steps, we also conduct dynamic multiplier analysis for the exogenous RPS policy variable. We follow Algorithm 2 in Ocampo and Rodrıguez to conduct this analysis.[62] This algorithm is as follows:

Algorithm 2 Identification by Long-Run Restrictions

1. Estimate the reduced form of the VAR-X model.
2. Calculate the VMA-X representation of the model (matrices $\boldsymbol{\psi}_i$) and the convariance matrix of the reduced form disturbance ε (matrix Σ).
3. From the Cholesky decomposition of $\boldsymbol{\psi}(1)$ and $\Sigma\boldsymbol{\psi}(1)$ calculate matrix $C(1)$

$$C(1) = \text{chol}(\boldsymbol{\psi}(1)\Sigma\boldsymbol{\psi}'(1))$$

4. With the matrices of long run effects of the reduced form, $\boldsymbol{\psi}(1)$, and structural shocks, $C(1)$, calculate the matrix of contemporaneous effects of the structural shocks, C_0.

$$C_0 = [\boldsymbol{\psi}(1)]^{-1}C(1)$$

5. For $i = 1, \ldots, R$ with R sufficiently large, calculate the matrices C_i as:

$$C_i = \boldsymbol{\psi}_i C_0$$

Identification is completed since all matrices of the structural VMA-X are known.

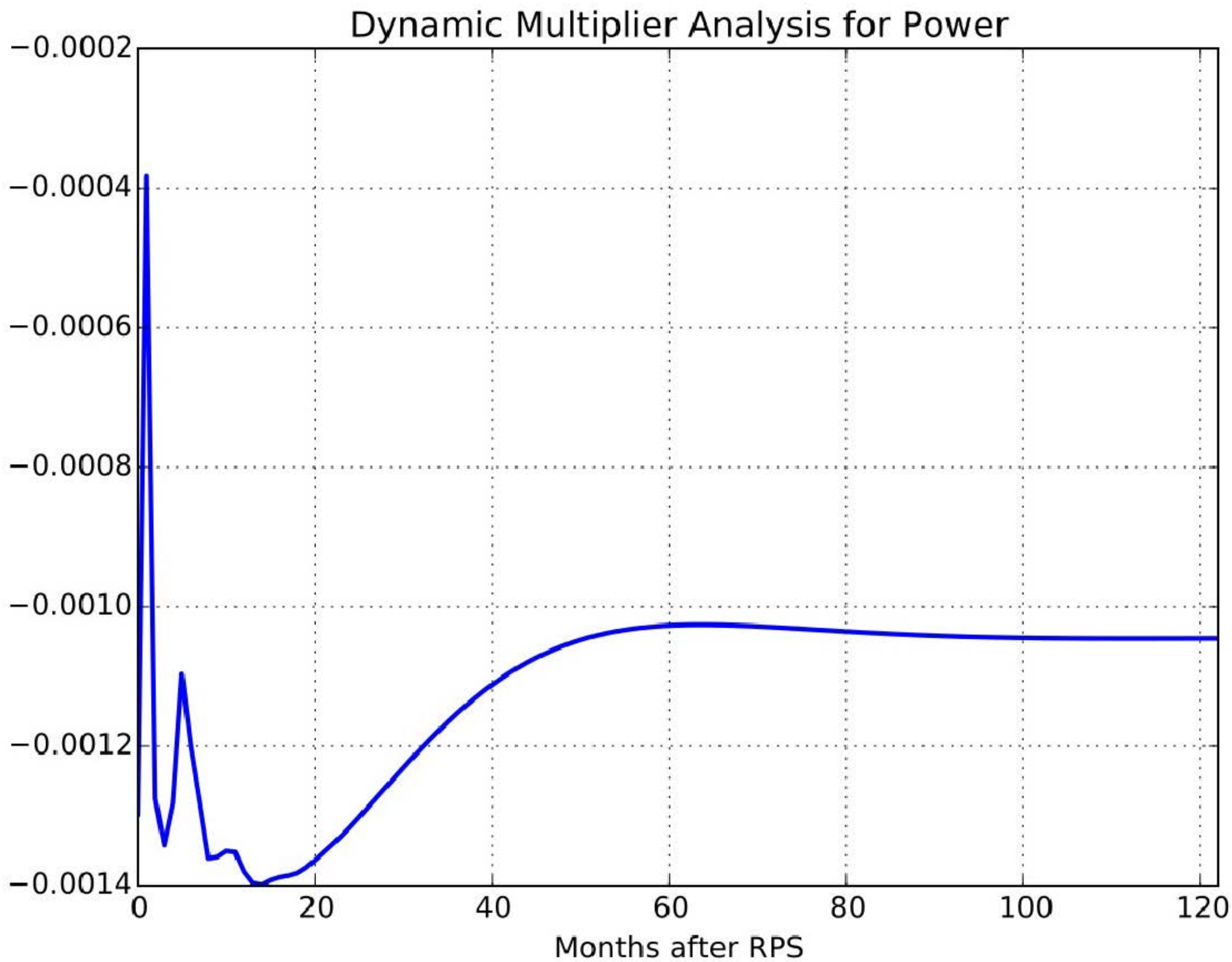
We set R = 120 months after an RPS to estimate the cumulative, or long-run effects of an RPS enactment for dynamic multiplier analysis.

[62] Ocampo, S., & Rodríguez, N., *op. cit.*

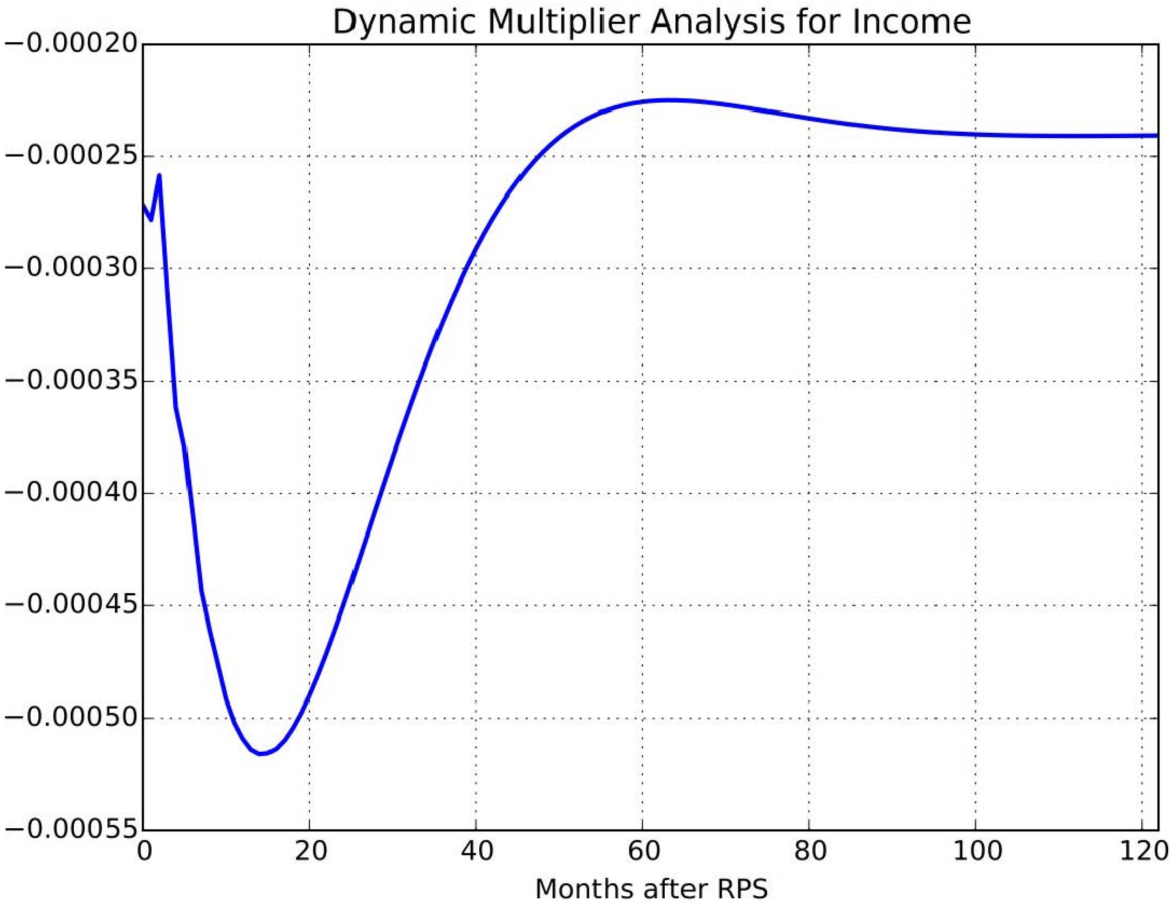
APPENDIX C

GRAPHICAL ANALYSIS OF THE DYNAMIC MULTIPLIER ANALYSIS

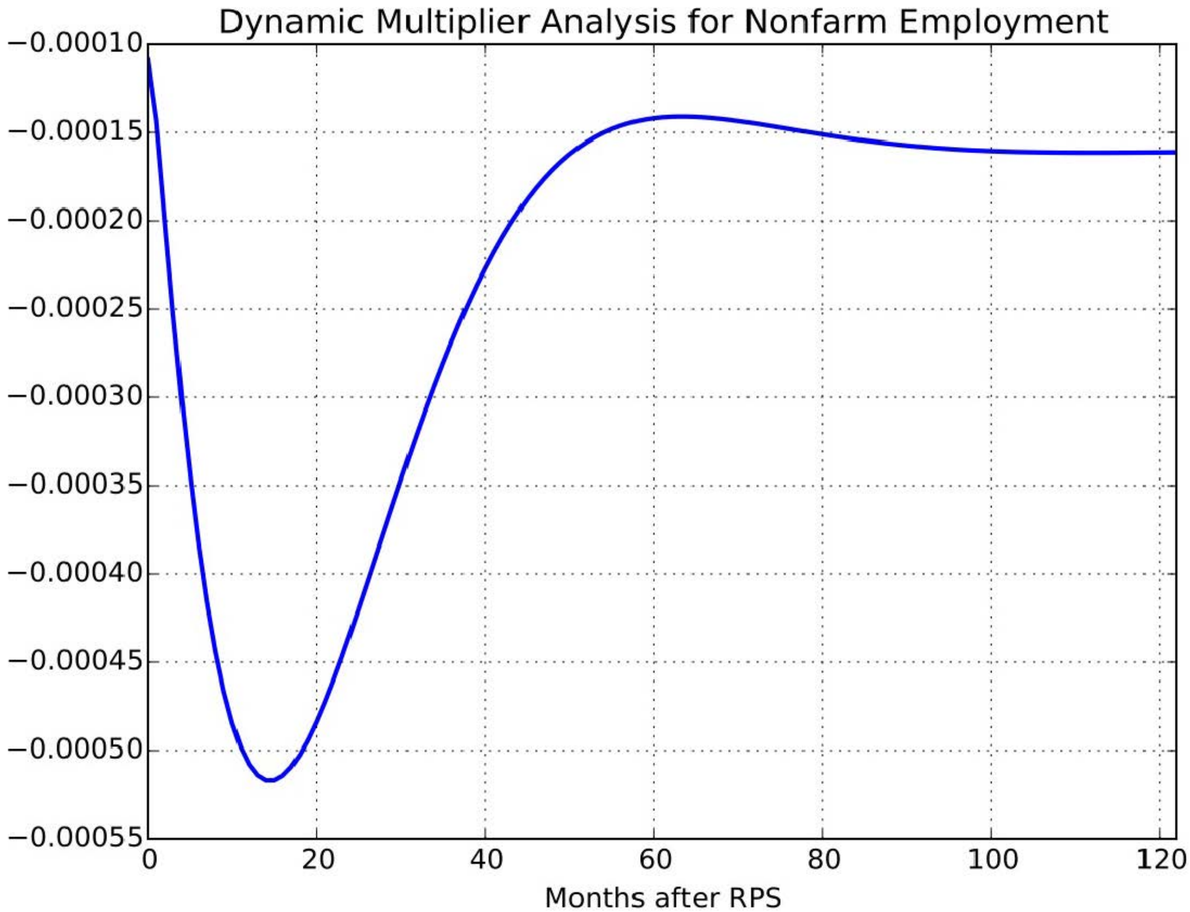
Below we present in graphical form the dynamic multiplier analysis for each of the five state macroeconomic variables. This analysis strengthens the evidence of a severely deleterious effect of an RPS policy. For electricity sales, real personal income, and non-farm employment the response to an RPS is an initial sharp decline lasting for several years and the long-run effect is a large and lasting decline. Manufacturing demonstrates the same initial sharp decline in response to an enacted RPS, but does show some recovery, after several years, though still never returns to levels prior to the RPS. However, the unemployment rate demonstrates a steadily increasing rate that cumulates into a large increase in state unemployment.



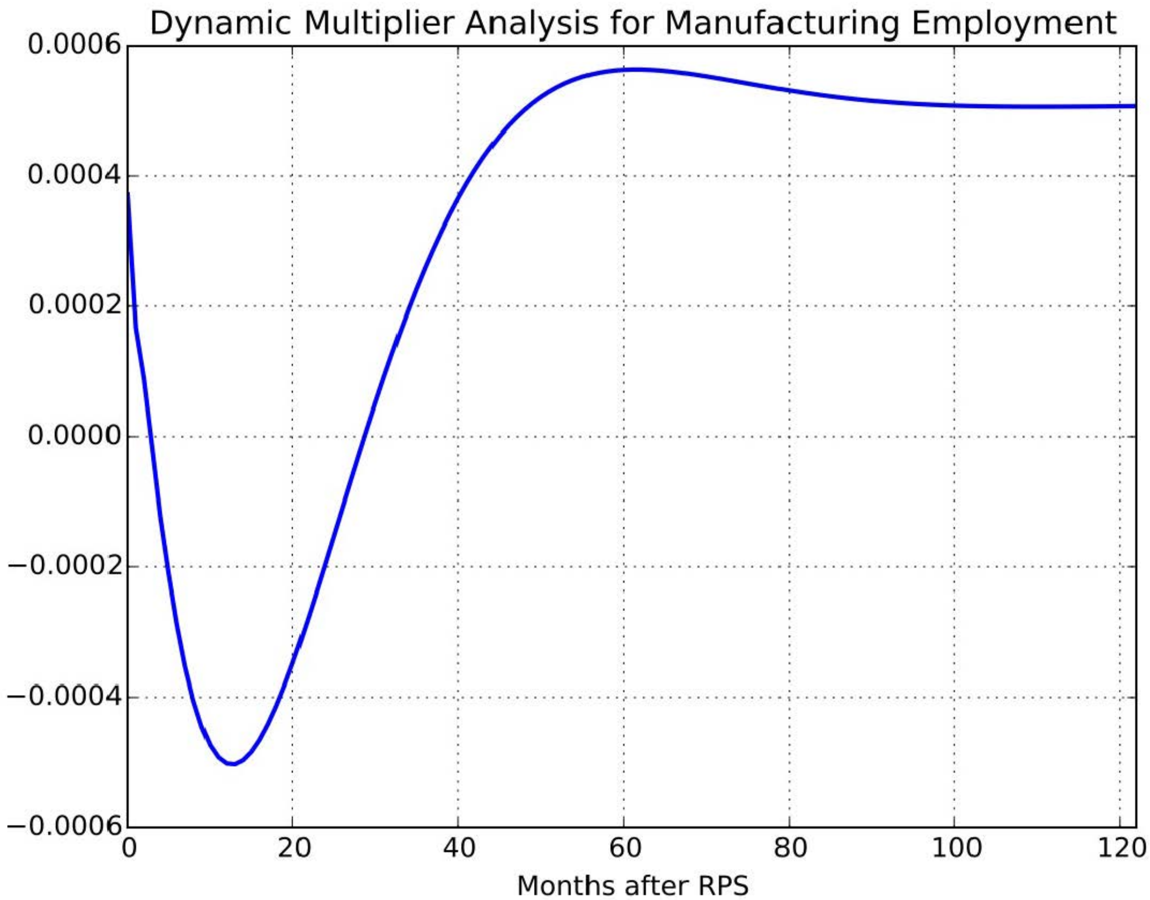
Dynamic Multiplier Analysis for Electricity Sales.



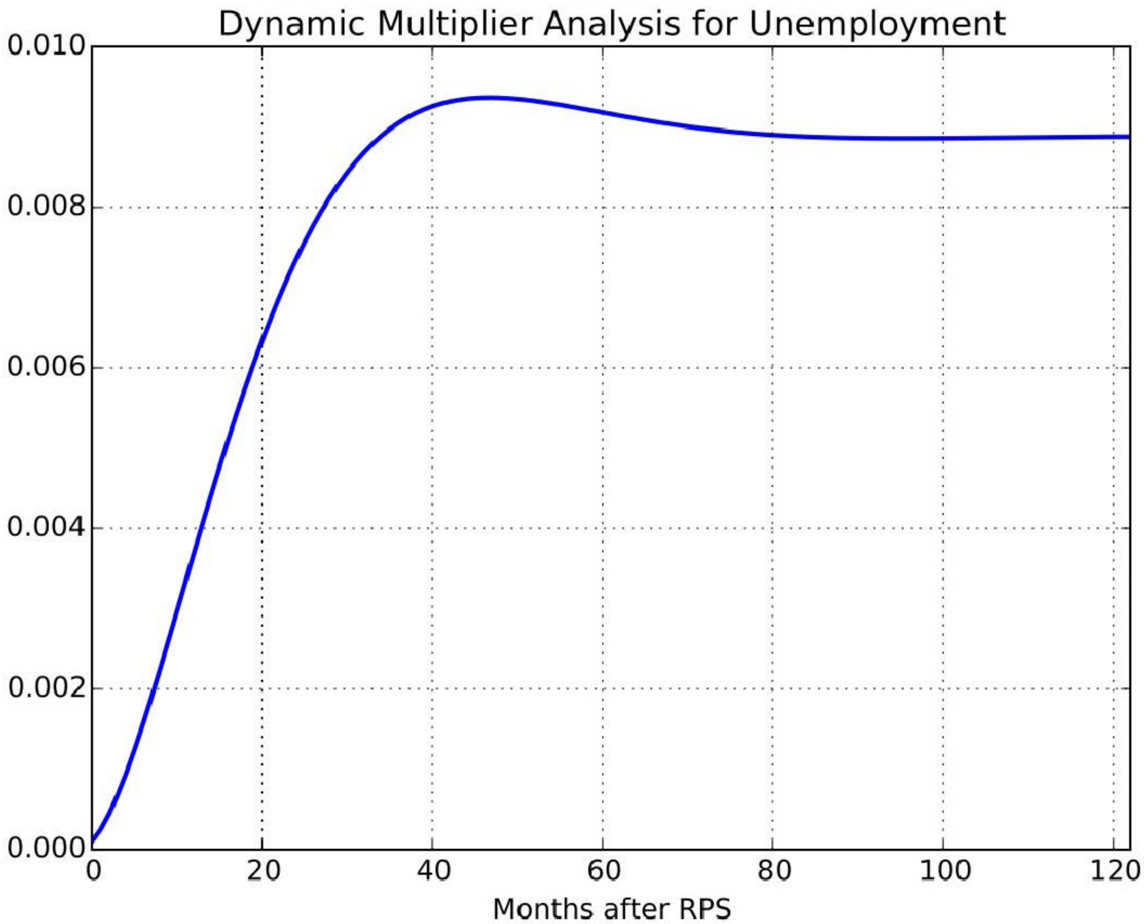
Dynamic Multiplier Analysis for Real Personal Income.



Dynamic Multiplier Analysis for Non-farm Employment.



Dynamic Multiplier Analysis for Manufacturing Employment.



Dynamic Multiplier Analysis for the Unemployment Rate.

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