

# THE HYDRO EFFECT

## -DO THE SHORT TERM HYDROLOGICAL BALANCE AFFECT THE PRICES OF FUTURE AND FORWARD CONTRACTS AT NORD POOL?

SIRI LUNDE HEGGEBØ

NORWEGIAN UNIVERSITY OF LIFE SCIENCES  
DEPARTMENT OF ECONOMICS AND RESOURCE DEVELOPMENT  
MASTER THESIS 30 CREDITS 2011



## Sammendrag

Denne oppgaven ser på om fyllingsgraden og tilsiget i Norge, Sverige og Finland har påvirkning på de finansielle kontraktsprisene på Nord Pool. Hoved hypotesen er:

*Er den kortsiktige hydrologiske balansen bestående av fyllingsgrad, tilsig og snømengde en god indikator på forskjellen som er mellom spot pris og pris på de finansielle kontraktene på Nord Pool?*

Temaene nedbør, fyllingsgrad, tilsig og snømengde i fjellene er hyppig brukt når man diskutere strømpriser. Den elementære modellen for hydroenergi sier at inntekt i spot markedet påvirkes av mengden lagret vann, tilsig og hvor mye vann som brukes i produksjon. Teorien om forholdet mellom spot prisen og prisen på en finansiell kontrakt sier at denne avhenger enten av fordelene ved å ha vann klar til produksjon om det ikke er fare for oversvømmelse i vannmagasinene, eller alternativkostnaden forbundet med oversvømmelse om det er fare for dette. Dette indikerer at det som påvirker inntekten for spot prisene og skal være med å drive prisene i det finansielle markedet, men i varierende grad.

Metoden brukt i denne oppgaven er økonometrisk analyse. Det er totalt brukt tjue ulike modeller, analyser for hver av de fem kontraktstypene; daglig, ukentlig, månedlig, kvartalsvis og årlig.

Analysen viser at de hydrologiske faktorene alene ikke er nok til å forklare forskjellen mellom spot og kontraktspris. De hydrologiske faktorene påvirker også de forskjellige kontraktstypene i forskjellig grad. Den daglige kontrakten virker ikke å bli så mye påvirket, men effekten er større i de ukentlige, månedlige og kvartalsvise kontraktene. Den årlige kontrakten ser heller ikke ut til å bli påvirket i stor grad. Et annet funn er at fyllingsgrad og tilsig ser ut til å påvirke mer enn energimengden i snøen på fjellet, og at fyllingsgrad forklarer mer enn tilsig.

## Abstract

This thesis is looking into if reservoir level and inflow for Norway, Sweden and Finland, and the energy equivalent of the snow in the mountains of Norway effects the future and forward prices at Nord Pool. The main thesis is:

*Is the short term hydrological balance of reservoir, inflow and snow a good measurement for the adjustment made to the spot price to get the future price?*

The theme of rainfall, reservoir levels and how much snow is going to melt in the spring is always a hot subject when talking about electricity prices. The basic hydropower model states that the income at the spot market is affected by stored water, incoming water and how much water is used in production. The theory of spot-future parity states that the future price is a function of the spot price and, either the advantage of holding on to water if no probability of overflow, or the alternative cost of an overflow if there is a probability of this. This indicates that the future price should be a factor of the spot price and the factor that drives this price, but to various degrees.

The method used in this paper is econometric analysis. We have all together twenty models that have been analyzed for each of the five contract types; daily, weekly, monthly, quarterly.

The analysis in the paper show that the hydrological factor alone are not enough to explain the future-spot parity and how future prices are different from spot prices. The hydrological factors also affect the different contracts to different degrees. The daily contract does not seem to be affected much by the observed hydrological factor. The weekly, monthly and quarterly contracts however seems to be affected to a larger degree. The yearly contract again does not seem to be affected that much as it has a longer time span. Another finding is that reservoir level and inflow seems to affect more than the snow in the mountains, and that reservoir level explains more of the price than the inflow.

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## Chapter 1, Problem

### Relevance

Electricity is one of our basic goods in the developed part of the world. We use it to get heat, light and to power a numerous of other devices we use on a daily basis. In the Nordic countries electricity is traded at Nord Pool spot exchange in a day-ahead-market.

As the Nordic countries have large variations in living conditions through seasons, the inhabitants in these countries are particularly engaged in electricity prices. Especially during the winter time these countries have the need for huge amounts of electricity for heating.

The Nordic power market includes power produced by many technologies. Denmark has lots of wind power, Finland and Sweden has a combination of hydropower and thermal power, and Norway has almost only hydropower. This large fraction of hydropower makes the amount of rain and snow a constant topic in discussing electricity prices. Each year there are reports on how much snow there is in the mountains, what the reservoir level is, and how much rain can there be expected. All these factors are important when it comes to how much electricity can be produced which determine the supply side of the market equilibrium, and hereby affect the price.

Suppliers are the ones that produce the actual electricity, but the consumers that operate at Nord Pool are actually the big electricity companies that sell electricity to private and corporate customers that actually consume the power. These companies buy their electricity both at the spot market, but a large fraction of the power is traded through financial contracts to create predictability for future costs. Financial contracts can also be used by producers to secure future income.

NASDAQ Commodity Exchange owns Nord Pool Spot Exchange, and also offers a broad specter of future- and forward contracts traders in the market use to secure spot prices in the future. The financial market is also open for speculators, which adds liquidity to the market. Most producers and consumers at the spot exchange secure a considerable part of their trades, the price for financial instruments is especially important for consuming companies' ability to turn profits as they deliver electricity to private consumers and other businesses.

As each winter approaches and the fear of high electricity prices drives the attention of all consumers to the hydrological balance, does this affect prices at the financial market as well?

## Hypothesis

The theory of hydro economics states the spot prices are affected by the hydrological balance, is there is more water available prices go down if demand is unchanged. The theory behind the spot-future parity states that the price of a future contract is the result of the spot price adjusted for storage costs and convenience yield. Both the storage costs and the convenience yield in hydropower are connected to the available amount of water at any given time. Is the short term hydrological balance of reservoir, inflow and snow a good measurement for the adjustment made to the spot price to get the future price?

- Does an increase in reservoir levels affect prices?
- Does a high inflow of water to reservoirs affect prices?
- Is there an effect of snow in the mountains on the future- and forward prices?
- Are different contracts with different time aspects affected by different hydrological factors?

## Chapter 2, Introduction

### Hydropower

To produce electricity generators need a primary energy source that can drive the turbines. Hydropower is based on water getting energy from waterfalls by gravity, and the energy can come from both unregulated river flows and regulated dams with limited storage capacity.

Hydropower has several characteristics which defines the market. First of all hydropower has high fixed cost regarding investments, these are also sunk costs that is irreversible when the investment is made. Second, the storage of water is complicated as there is high uncertainty regarding inflow to dams. Third, there are limitations to the grid which means there are limits on how much electricity can be sent from one location to another. Last we have that produced electricity must be equal to consumed electricity at all times as there are no way of storing electricity in the grid. (Førsund 2007)

Hydropower does also have a characteristic that distinguish it from forms of producing electricity, hydropower plants are fairly easy and cheap to shut down and start up compared to thermal energy. This makes hydropower a highly sought after form of producing electricity as this production has to be monitored and adjusted constantly due to the fact that produced electricity must be equal to consumed electricity at all times.

#### *Hydropower model*

The basic hydropower model uses these notations:

$e_t^H$  – Electricity produced from regulated hydropower

$e_t^R$  – Electricity produced from unregulated hydropower

$R_t$  – Reservoir level at time t

$\bar{R}$  – Reservoir capacity

$w_t$  – Inflow to reservoir

$\bar{e}^H$  – Production capacity for regulated hydropower

First we have the objection function; we want to maximize our earnings.

$$\max \sum_{t=1}^T \int_0^{e_t^H + e_t^R} p(z) dz$$



We also have to consider multiple constraints regarding storage and production. These constraints are:

- Storage constraint  $R_t \leq \bar{R}$

The storage constraint states that there is a maximum reservoir level we need to consider

- Water constraint  $R_t = R_{t-1} + w_t - e_t^H$

The water constraint states that the water stored at the end of a period is the sum of storage at the end of last period and the inflow in this period, minus the water used in production this period

- Production constraint  $e_t^H \leq \bar{e}^H$

The production constraint states that there is a maximum production capacity to be considered.

From this we get our model which we solve with regards to what conditions we have:

$$\max \sum_{t=1}^T \left[ \int_0^{e_t^H + e_t^R} p(z) dz \right] - \gamma_t [R_t - \bar{R}] - \lambda_t [R_t - R_{t-1} + w_t - e_t^H] - \sum_{t=1}^T \rho_t [e_t^H - \bar{e}^H]$$

(Førsund 2007)

As Førsund shows in his model electricity prices are highly affected by the access to water, the amount of water stored, and how much water that is added at any given period.

## Organization of the Nordic power market

The Nordic Power market consists of a financial market for futures- and forward contracts, a day-ahead spot market and an intra-day balancing market called Elbas. (Spot 2011)

In the day-ahead spot market buyers and seller has to submit their bids and offers before 12:00 the previous day. After all bids and offers are presented supply and demand curves are made to find the clearing price for each area and time period the following day, results are ready at approximately at 13:00. All countries are divided into areas with its own spot price due to constraints in the power grid. Likewise each day is divided into 24 time periods where the time from 08:00 to 20:00 are peak hours, when consumption is at its highest, and the hours before and after are off-peak. (Spot 2011)

The intraday Elbas market makes for only a fraction of the traded electricity. The main function for this market is to adjustments since consumption rarely s as expected the day ahead. Here only one participant buys or sells electricity according to needs in the market. (Spot 2011)

Futures and forward contracts are traded at NASDAQ OMX at real time. Here both the physical participants and speculators can trade in contracts to try and beat spot prices in the future. Since electricity can't be stored the contracts cash settlements against the system price at the spot exchange. To hedge against difference in area prices there are also Contracts for Difference. (Spot 2011)

### **Nord Pool and its history**

In 1991 the Norwegian government decided to deregulate the electricity market. This meaning the price of electricity should not be decided by the government but be the result of a market consisting of producers and consumers. In 1993 Statnett marked AS was established as an independent company, and in 1995 the framework for an integrated Nordic power market was made. (Commodities 2011)

In 1996 Norway and Sweden established Nord Pool ASA, a joint power exchange for the two countries. The first seasonally based financial forward contracts was introduced in 1997, these contracts had a time horizon of three years. Finland and western Denmark joined the exchange in 1998, and in the same year annual forward contracts was introduced. (Commodities 2011)

The intraday market, Elbas, was first introduced in Finland and Sweden in 1999. The joint Nordic power exchange was completed in 2000 when also Eastern Denmark joined Nord Pool. The same year contracts for difference were introduced, making it possible to hedge for spot prices in a particular area. (Commodities 2011)

In 2001 Nord Pool ASA applied to be a licensed clearing house, and this became official in 2002. This also meant that the clearing house and the spot market were demerged into separate companies. The quarterly and monthly forward contracts were introduced in 2003, and in 2006 the time horizon was extended to 6 years. (Commodities 2011)

In 2008 NASDAQ OMX acquired Nord Pool Clearing ASA, Nord Pool consulting and the international products, and merged them into NASDAQ OMC Commodities AS. In this process Statnett and Svenska

Kräftnett also an option to sell Nord Pool ASA. The next year Norway joined Elbas, and in the summer of 2010 NASDAQ OMX acquired Nord Pool ASA from after the Norwegian and Swedish owners decided to exercise their option to sell. (Commodities 2011)

### **Futures and forward contracts at Nord Pool**

The futures and forward contracts at Nord Pool are both standardized contracts. The contracts have the same specification when it comes to volume and quality (there is no quality difference), but they have different settlements and the delivery periods vary. However all the contracts have cash settlement as electricity is a commodity which cannot be stored. The settlement is calculated against the system price at the spot market throughout the settlement period. (Commodities 2011)

Future contracts include contracts for days and weeks. These contracts have cash settlement both on a daily mark-to-market basis and final spot reference that starts at the expiry date of the contract. Forward contracts are contracts for months, quarters and years. These contracts do not have a realized settlement towards the system price in the trading period, but realizes cash settlement in the delivery period. As it is only settlement process and maturity time that differs for the different future and forward contracts at Nord Pool the other factors in the spot-future parity are the same. (Commodities 2011)

The storage cost for hydropower is connected to the storage of water in reservoirs. A reservoir has high investment costs, but the actual storage costs for water when the reservoir is operative are close to zero. On the other hand a reservoir can only hold a certain amount of water. If this level is exceeded water will be spilled, and the power company will not gain any income from this water. Therefore the cost of carry is equal to the alternative cost, the risk of the reservoir overflowing and water being spilled. (Førsund 2007)

The advantage of having water to produce electricity contracts derives from the fact that electricity prices are highly volatile to natural changes in temperature, day light etc. This gives the holder of water in reservoir the benefit of being able to produce electricity at a time with high prices. (Førsund 2007)

As we know water is essential for the future contracts at Nord Pool due to its high fraction of hydropower energy. Water is mainly stored in reservoirs, but as the Nordic country as a cold climate with snow during the winter water can also be stored as snow in the mountains. The snow will effect both the cost of carry, through the danger of overflow when it melts, and the convenience yield, through water in reservoirs in the spring.

### **Why trade with futures and forward contracts?**

Future and forward contracts are used by different participants for different reasons. A participant that also participates in the physical market uses the financial market to secure the price of electricity in the future. They can spread the risk by investing in different contracts, and usually most of their sold bough electricity is hedged at a previous time. This creates more security, and if luck firms can “beat” the spot price and increase profits. (Hull 2008)

## Chapter 3, Theory

### Basics for future contracts

Future contracts are mainly financial instruments used to secure prices in the future. The contracts are standardized regarding volume, quality, time and place of delivery, and they go through a clearing house which bears the actual risk and acts like the counterpart in each trade. Forward contracts however, are not standardized, and are entered between seller and buyer without a clearinghouse as an impartial “middle man”. Here the buyer and seller each take on their own risk, and the contract are specified to their wishes instead of being a predetermined standard. (ZVI Bodie 2009)

The time from when a future/forward contract is bought or sold to the settlement period/point starts is called maturity time. During this time the price of the contract can be highly volatile, but theory states that both the volatility and the basis will decrease and get close to zero as the maturity time is running out. (ZVI Bodie 2009)

Basis is the difference in the spot price and the future price. This is often looked at as a premonition of how the spot price will develop in the future. However there are several factors contributing, and the basis varies throughout the maturity time. (ZVI Bodie 2009)

### Mark to market

Marking to market is the process where loss and profit is accrued to traders who trade in future contracts. The most common way is that the traders are required to have a margin account with the clearing house. The margin account acts like a security with highly liquid assets, which is a way to secure that the trader can meet obligations brought on by the future contracts. Since there is a possibility of loss both when being long and short in a future contract all traders are required to post this security. (ZVI Bodie 2009)

Each day a future contract is traded a trader either gains profits or has to take a loss. This profit/loss is settled against the margin account, and this is called mark to market. This realization makes it easier to control that traders can meet their obligations, and it also makes it easier tax-wise as we can see the profits/losses for each year even though maturity time can stretch over two/several years. If the margin account falls under a certain level set by the clearing house the trader receives a margin call. This level is often given in percentage of the total investment, and varies by how volatile the prices of the contract are. When receiving a margin call the trader has to transfer more assets or the position will be terminated. This ensures that the trader's losses are covered, and thereby eliminating the risk of the clearing house. (ZVI Bodie 2009)

## Cash and physical delivery

As mentioned before future contracts are standardized regarding volume, quality, time and place of the delivery. This suggests that if we hold a long position in a future contract we have to go to a specified place to pick up a certain amount of a certain quality of a commodity. However this is not always doable as some commodities are not storable. In these cases the future contract has a cash settlement where the trader is paid a profit/has to pay the loss when comparing the amount paid for the contract to the spot price at the settlement period/point. (ZVI Bodie 2009)

## Hedging and speculation

Hedger and speculators are the two types of traders that operate in a future market. The hedger is a producer or a consumer that needs to use the future contracts to protect against a rise or fall in spot prices. A speculator on the other hand trades in the market purely with the goal to gain a profit. It can be argued that speculators should not be allowed into the market, but the fact is that they bring liquidity and increase the volume in the market. (ZVI Bodie 2009)

## Spot-Future parity

The spot-future parity is derived from the idea that there can be no arbitrage. No arbitrage means that the rate of return on a position in the future market is equal to the rate on other risk-free investments, if this is not the case investors will exploit until the balance is restored. To meet this idea we have four assumptions that must be true for all market participants:

1. The market participants are subject to no transactions costs when they trade
2. The market participants are subject to the same tax rate on all net trading profits
3. The market participants can borrow money at the same risk-free rate of interest as they can lend money
4. The market participants take advantage of arbitrage opportunities as they occur

(Hull 2008)

For our model we will use these notations:

$t$  – time, 0 indicates today, and  $T$  indicates point of maturity,  $t = 0, 1, \dots, T$

$F_t$  – future price at time  $t$

$S_t$  – Spot price at time  $t$

$r$  – risk free interest rate

$q$  – dividend yield rate

$u$  – storage costs as a proportion of the spot price

$y$  – convenience yields

$c$  – cost of carry

The basic pricing model for future contracts states that future prices increase at a rate equal to  $r-q$  with the maturity of the contract. (Hull 2008)

$$F_0 = S_0 e^{(r-q)T}$$

When it comes to future contracts for commodities however we also need to consider the cost of storage as this can be significant and the benefits of holding a commodity as this can be used instantaneously if needed. (Hull 2008)

The storage increases the future price as the holder of a future contract does not need to take the storage costs as a holder of the physical commodity has to. Storage costs as a fraction of the spot price increases the rate at which the future price increase. (Hull 2008)

$$F_0 = S_0 e^{(r+u)T}$$

Convenience yield is the benefit of holding the actual physical commodity. As mentioned holding the physical commodity makes it possible to use it at any time in contrast to a holder of the future contract that has to wait until maturity time is up. During the maturity there are a number of risks the holder of a future contract is exposed to. The biggest risk is that there can be a shortage of the commodity. Crops might fail, environmental factors can affect delivery or the holder of the contract might just run out of commodity before the maturity point. (Hull 2008)

$$F_0 e^{yT} = S_0 e^{(r+u)T}$$

This can be rewritten with the term cost of carry  $c = r + u$

$$F_0 = S_0 e^{(c-y)T}$$

Electricity is initially a non-storable commodity, at least for consumers. The producers however can to some extent store the inputs needed in the production. This storage is in hydro energy done through huge reservoirs made by the producers, but also nature stores water during the winter as snow. (Hull 2008)

The construction of reservoirs requires large investment costs, but as soon as the reservoir is finished the marginal cost of storage is equal to zero as long as the reservoir does not overflow. If the reservoir for any reason does overflow the marginal cost of storage equals the alternative cost we get from the overspill, the lost income we could have gained from the water had it been used to produce electricity.

When the risk of overflow during a contracts maturity period is close to zero we get the future-spot parity of:

$$F_0 = S_0 e^{(-y)T}$$

Here  $y$  goes towards zero when reservoir fillings are high, and becomes positive as people are getting worried about the supply situation. When reservoir fillings get really low  $y$  increases drastically to keep reservoir levels from dropping to zero.

If there is a risk of overflow however  $y$  is zero and we get the future-spot parity of:

$$F_0 = S_0 e^{(Pr\ obx E(S_T))T}$$

Where  $Pr\ obx E(S_T)$  is the probability of overflow, in other words the expected marginal cost.



## Model

When analyzing datasets we need to identify the properties of our datasets. We have observations over time, but we have multiple observations at each point in time. Even though we are not interested in the effect over time, panel data have certain properties that we need to take into consideration when analyzing the panel data. We will return to these properties later.

Before analyzing the actual data we need to combine our two previous models for future pricing. We have two different models occurring at two different states, if there is not (1) or if there is (2) a probability of overflow.

$$F_0 = S_0 e^{(-y)T} \quad (1)$$

$$F_0 = S_0 e^{(Prob(E(S_T)))T} \quad (2)$$

We can combine these

$$F_0 = S_0 e^{(\rho[Prob(E(S_T)) - [1-\delta]y)T} \quad \rho = \begin{cases} 0 & \text{if } Prob(overflow) = 0 \\ 1 & \text{if } Prob(overflow) > 0 \end{cases}$$

We see that if there is not a critical danger of an overflow we get the future spot parity with convenience yield, and likewise if there is a crucial danger of overflow we get the future spot parity with the alternative cost presented with an overflow.

That the convenience yield and alternative cost brought on by the probability of overflow have an exponential form is consistent with the theory that they are not linear in their values. When the reservoir level is high there is not any advantages of stocking water, and at the same time there is not an alternative cost as long as there is not a danger of overflow. However, if reservoir levels are low the advantages of stocking water are high as people are getting scare that the reservoirs may run out, their willingness to pay increases and drive the prices upwards. If there is a probability of overflow the potential cost will increase, and we also get a decrease in the willingness to pay. This means that our variables are more likely to take on an exponential form than to be linear.

In this analysis however we do not want to measure the effect spot price has on the future price, but if the hydrological factors combined with days to maturity can be used as measurement for the convenience yield and the alternative cost with the probability of overflow. We also need to put the equation in a form that is possible to analyze with statistical software. First we make the equation onto log form and then rearrange so that we can combine the future price and the spot price in one term:

$$\ln F_0 = \ln S_0 + (\rho [\text{Prob}(S_T)] - [1 - \delta]y)T$$

$$\ln F_0 - \ln S_0 = (\rho [\text{Prob}(S_T)] - [1 - \delta]y)T \quad \rho = \begin{cases} 0 & \text{if } \text{Prob}(\text{overflow}) = 0 \\ 1 & \text{if } \text{Prob}(\text{overflow}) > 0 \end{cases}$$

As mentioned in the introduction the price of electricity is highly dependent on the variables in our dataset. From the model above we have a wide range of possibilities when it comes to analyzing our data. We have in all seven variables, seven seasonal variables and seven variables for difference, and from these we can create models suitable for analyzing. The different variables are:

*Name* – Name of contract , ENOM + type + maturity point

*Date* – Date of observation

*DTM* – Days to maturity (T)

*FP* – Price of contract (future or forward)

*SP* – Spot price

*ARLN* – average reservoir level in Norway

*RLN* – reservoir level in Norway

*RN* = *RLN* – *ARLN*, seasonal difference

*ARLS* – average reservoir level in Sweden

*RLS* – reservoir level in Sweden

*RS* = *RLS* – *ARLS*, seasonal difference

*ARLF* – average reservoir level in Finland

*RLF – reservoir level in Finland*

*RF = RLF – ARLF, seasonal difference*

*AIN – average inflow in Norway*

*IN – Inflow to reservoirs in Norway*

*IFN = IN – AIN, seasonal difference*

*AIS – average inflow in Sweden*

*IS – Inflow to reservoirs in Sweden*

*IFS = IS – AIS, seasonal difference*

*AIF – average inflow in Finland*

*IF – Inflow to reservoirs in Finland*

*IFF = IF – AIF, seasonal difference*

*AEESN – Average Energy equivalent of the snow in Norway*

*EESN – Energy equivalent of the snow in Norway*

*ESN = EESN – AEESN, seasonal difference*

The variables give us the possibility of analyzing if there is any effect in many different ways. To be able to draw any conclusions we need to analyze the variables separately and in different combinations. We will analyze models for actual observations, seasonal variables and difference variables that are the difference between the actual observation and the seasonal variable. We will also conduct analysis of reservoir level, inflow and snow all together and independently.

We have chosen to analyze the same models for all contracts to be able to get information from each and to compare the different type of contracts. The models we have chosen to analyze are:

- Test for the actual observations, all together and independently

$$\ln F_0 - \ln S_0 = (RLN + RLS + RLF + IN + IS + IF + EESN)DTM \quad (1)$$

$$\ln F_0 - \ln S_0 = (RLN + RLS + RLF)DTM \quad (2)$$

$$\ln F_0 - \ln S_0 = (IN + IS + IF)DTM \quad (3)$$

$$\ln F_0 - \ln S_0 = (EESN)DTM \quad (4)$$

- Test for the seasonal variables, all together and independently

$$\ln F_0 - \ln S_0 = (ARLN + ARLS + ARLF + AIN + AIS + AIF + AEESN)DTM \text{ (5)}$$

$$\ln F_0 - \ln S_0 = (ARLN + ARLS + ARLF)DTM \text{ (6)}$$

$$\ln F_0 - \ln S_0 = (AIN + AIS + AIF)DTM \text{ (7)}$$

$$\ln F_0 - \ln S_0 = (AEESN)DTM \text{ (8)}$$

- Test for the actual observations and the seasonal variables, all together and independently

$$\ln F_0 - \ln S_0 = (ARLN + RLN + ARLS + RLS + ARLF + RLF + AIN + IN + AIS + IS + AIF + IF + AEESN + EESN)DTM \text{ (9)}$$

$$\ln F_0 - \ln S_0 = (ARLN + RLN + ARLS + RLS + ARLF + RLF)DTM \text{ (10)}$$

$$\ln F_0 - \ln S_0 = (AIN + IN + AIS + IS + AIF + IF)DTM \text{ (11)}$$

$$\ln F_0 - \ln S_0 = (AEESN + EESN)DTM \text{ (12)}$$

- Test for the seasonal difference variables, all together and independently

$$\ln F_0 - \ln S_0 = (RN + RS + RF + IFN + IFS + IFF + ESN)DTM \text{ (13)}$$

$$\ln F_0 - \ln S_0 = (RN + RS + RF)DTM \text{ (14)}$$

$$\ln F_0 - \ln S_0 = (IFN + IFS + IFF)DTM \text{ (15)}$$

$$\ln F_0 - \ln S_0 = (ESN)DTM \text{ (16)}$$

- Test for the actual observations and the seasonal difference variables, all together and independently

$$\ln F_0 - \ln S_0 = (RLN + RLS + RLF + IN + IS + IF + EESN + RN + RS + RF + IFN + IFS + IFF + ESN)DTM \text{ (17)}$$

$$\ln F_0 - \ln S_0 = (RLN + RLS + RLF + RN + RS + RF)DTM \text{ (18)}$$

$$\ln F_0 - \ln S_0 = (IN + IS + IF + IFN + IFS + IFF)DTM \text{ (19)}$$

$$\ln F_0 - \ln S_0 = (EESN + ESN)DTM \text{ (20)}$$

Now we have defined the form of the models we want to use in our analysis, and stated that we are

dealing with panel data. Before we can draw any conclusions from our models we need to test the functional form for our models. The functional form needs to satisfy the following assumptions: (Wooldridge 2009)

1. Linearity and weak dependence
2. No perfect collinearity among the independent variables
3. Zero conditional mean of the disturbances
4. The error terms are homoscedastic
5. No serial correlation

Assumption number one includes to statistical tests. The first thing we need to do with our time series data is to test if we have stationary data or not. If the data are stationary they have the same distribution independently over time. In this analysis we have chosen to conduct a fisher test for analysing stationarity in panel data. (Wooldridge 2009)

$$\left. \begin{array}{l} H_0: \text{Not stationary data} \\ H_1: \text{Statinary data} \end{array} \right\} \text{Reject } H_0 \text{ if } p_{value} < \alpha$$

Note that this test is for the dataset, not for each model. We want to reject  $H_0$  in this test.

The next part of assumption one is to test if each model is linear in its parameters. To do this we conduct a Ramsey test: (Wooldridge 2009)

$$\left. \begin{array}{l} H_0: \text{Parameters are linear} \\ H_1: \text{Not linear parameters} \end{array} \right\} \text{Reject } H_0 \text{ if } p_{value} < \alpha$$

Assumption two states that there should be no perfect collinearity. To test for this we simply need to look at the estimation of our model and see if any of the variances are equal to zero. If this is the case assumption three does not hold. (Wooldridge 2009)

$$\left. \begin{array}{l} H_0: \text{all } \sigma^2_i \neq 0 \\ H_1: \text{One or more } \sigma^2_i = 0 \end{array} \right\} \text{reject } H_0 \text{ if not all } \sigma^2_i \text{ is different from zero}$$

Assumption three states zero conditional mean. This means that given any of the dependent values the expected value of the error term will be  $u$ . If assumption number four holds we have exogenous explanatory variables, and if it fails we have endogenous explanatory variables. To test assumption four we first predict the residuals, and then test if they are statistically significant different from zero: (Wooldridge 2009)

$$\left. \begin{array}{l} H_0: E(\varepsilon|x_i) = 0 \\ H_1: E(\varepsilon|x_i) \neq 0 \end{array} \right\} \text{Reject } H_0 \text{ if } p_{value} < \alpha$$

Assumption number four does not affect the actual estimates, but it does effect the calculations of T, F and  $\chi$  statistics. If hetroscedasticity is present we need to use robust standard errors when conducting other tests. Since this is a panel data we choose to estimate with robust standard errors adjusted for clusters. (Wooldridge 2009)

The last assumption states no serial correlation. This states that the error term at time period t-1 should not have any effect on  $y$  at time period t. To test for this we obtain residuals from our model and then test the lagged residuals in the model. If the residuals are individual statistically significant we do not have serial correlation. (Wooldridge 2009)

$$\left. \begin{array}{l} H_0: E(\varepsilon|y_i) = 0 \\ H_1: E(\varepsilon|y_i) \neq 0 \end{array} \right\} \text{Reject } H_0 \text{ if } p_{value} < \alpha$$

After conducting tests for to see if the assumptions hold we have a set of tests that will help us analyze the effect of our hydrological variables n the prices of future and forward contracts. First we conduct tests for individual significance. We compute T-statistics for all included variables, and compare them to the critical t-value:

$$\left. \begin{array}{l} H_0: \beta_i = 0 \\ H_1: \beta_i \neq 0 \end{array} \right\} \text{Reject } H_0 \text{ if } |T_{value}| > T_{\alpha/2}$$

Further we want to test if the included variables for reservoir level and inflow are jointly significant. To do this we conduct two F-tests, one for all reservoir level variables and one for the inflow variables.

$$\left. \begin{array}{l} H_0: \sum \beta_{RLi} = 0 \\ H_1: \sum \beta_{RLi} \neq 0 \end{array} \right\} \text{Reject } H_0 \text{ if } |F_{value}| > F_{\alpha/2}$$

$$\left. \begin{array}{l} H_0: \sum \beta_{Ii} = 0 \\ H_1: \sum \beta_{Ii} \neq 0 \end{array} \right\} \text{Reject } H_0 \text{ if } |F_{value}| > F_{\alpha}$$

When conducting the tests above we test against a chosen significance level,  $\alpha$ . The significance level means setting the acceptable probability of  $H_0$  in fact being true when we chose to reject it. The practical approach is that the rejection of  $H_0$  is correct in  $(1-\alpha)\%$  of the tests. The models above are tested to see if we can use variables for reservoir level, inflow and energy equivalent of snow in the mountains to represent the value of convenience yield and the alternative cost regarding the danger of overflow. In the analysis we want to minimize the chance of rejecting a model when it is in fact valid, and therefore we choose the significance level of 1%. In the other tests we also want to minimize the chance of rejecting  $H_0$  when it is in fact true. The only time we actually want to reject  $H_0$  is when we are testing for stationary variables, but as we want to be accurate, we use a significance level of 1% when conducting all tests. (Wooldridge 2009)

Another important factor of the panel data is that they need to be balanced in order to carry out the tests with the statistical software. A balanced panel data set is a dataset with the same number of observations each time period. We will return to how we have chosen to keep each dataset balanced in chapter four.

## Chapter 4, Datasets

Nord Pool has all together five different future and forward contracts, so in this analysis we have five different datasets. All datasets contains the variables we used to make the models.

The data for reservoir levels, inflow and energy equivalent of the snow has weekly observations. The contracts are traded every work day throughout the year, but in this analysis I have chosen to include the observations for Wednesdays. This is due to the fact the Norwegian energy resources and energy directory releases the number for the reservoir level each Wednesday at 13:00. This number is the focus for most discussions regarding electricity prices both in Norway and to some extend in the whole Nord pool area.

### Reservoir Level

The data for the reservoir level is collected from the Norwegian water and natural resource directory, the Swedish energy report and the Finnish environment institute. Reservoir is total water stock in percentage of the maximum water stock. We also have season variables where we found the average reservoir level from 1995 through 2010, with the exception of Finland where we are missing values for the years 1995 and 2001.

As can be seen in figures one, two and three the red line which is the average reservoir level for each country shows that the reservoir level moves in cycles with periods of large inflow followed by periods where reservoirs are drained when producing electricity. The actual reservoir level also follows this path, but deviates to various degrees from the average.

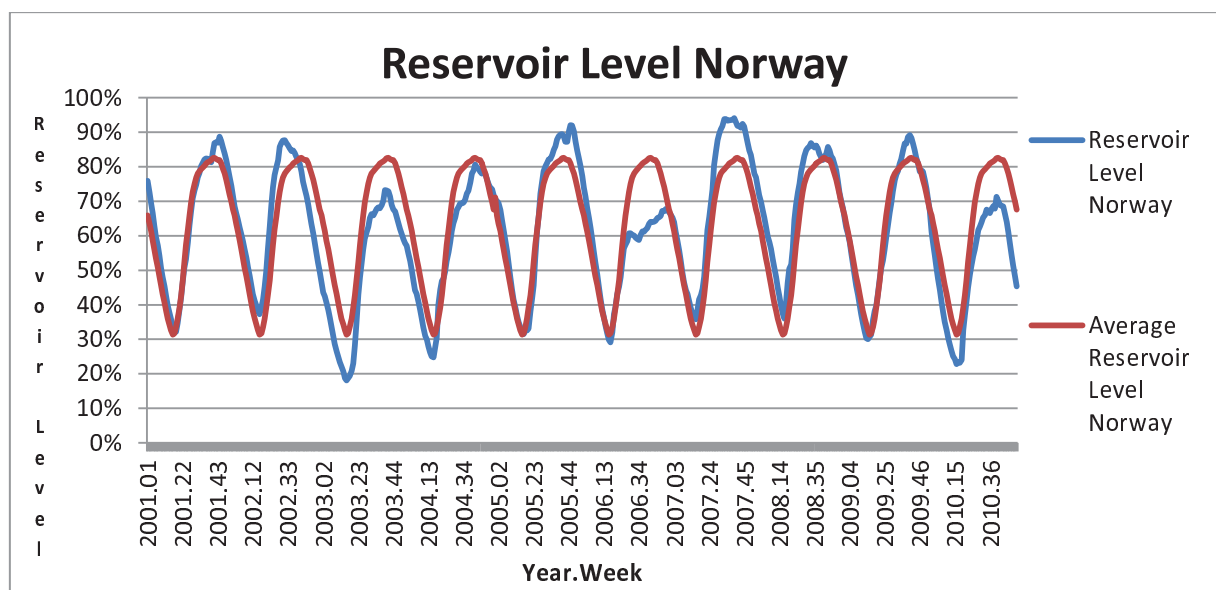




Figure 1: Actual and average reservoir level Norway

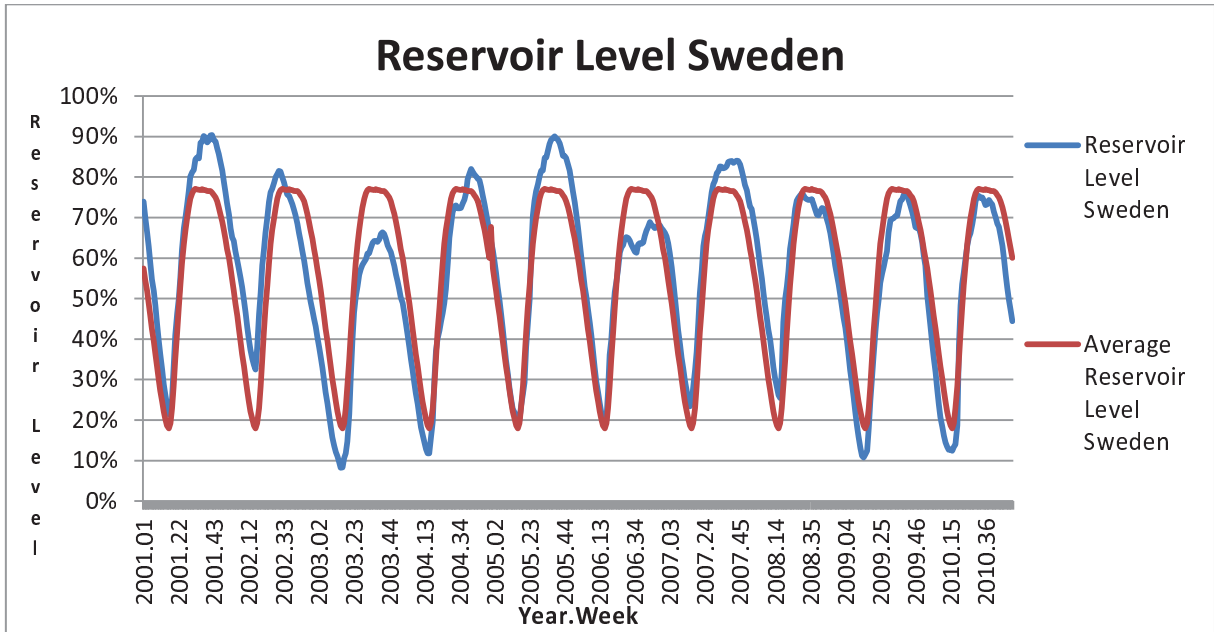


Figure 2: Actual and average reservoir level Sweden

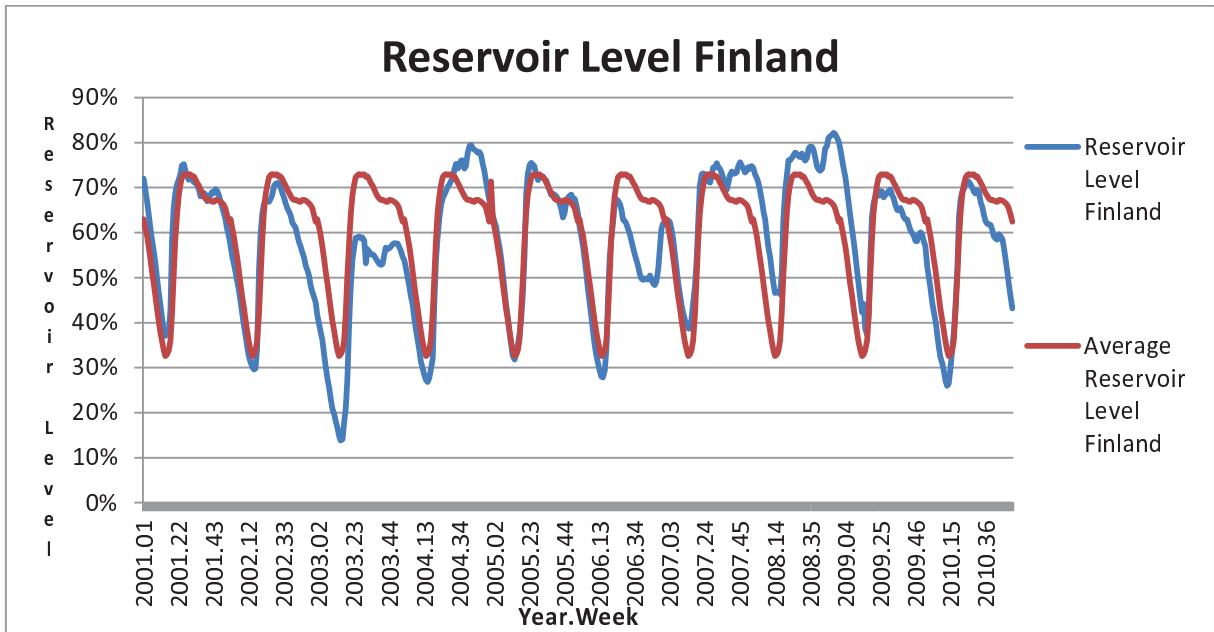


Figure 3: Actual av average reservoir level Finland

## Inflow

The data for the inflow is collected from the Norwegian water and natural resource directory, the Swedish energy report and the Finnish environment institute. The inflow is measured in % of the maximum water stock. We also have season variables where we found the average inflow for Norway and Sweden from 1995 through 2010, and for Finland from 2001 through 2010.

In figures four, five and six we see that also the inflow moves in cycles where we have periods with more water coming into the reservoirs followed by periods where the inflow is lower. We see that the actual inflow follow the same cycles as the average, but it deviates more than the reservoir level from its average. This is due to the fact the inflow is highly volatile, where rain and snowmelt deviates quite a lot from a period one year to another period next year.

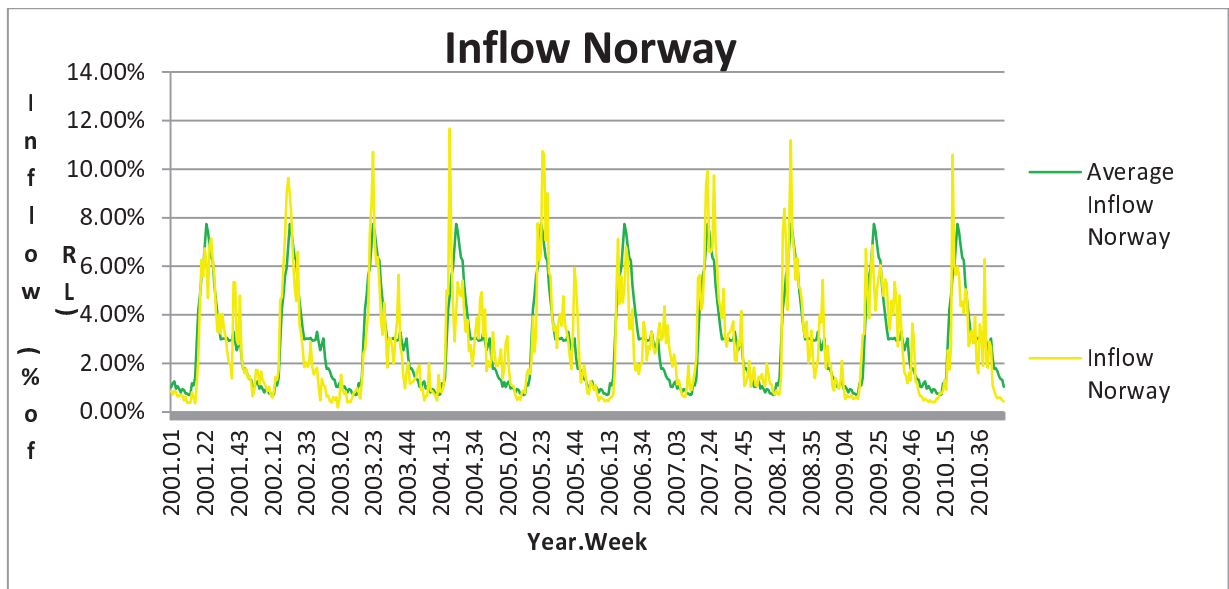


Figure 4: Actual and average Inflow Norway

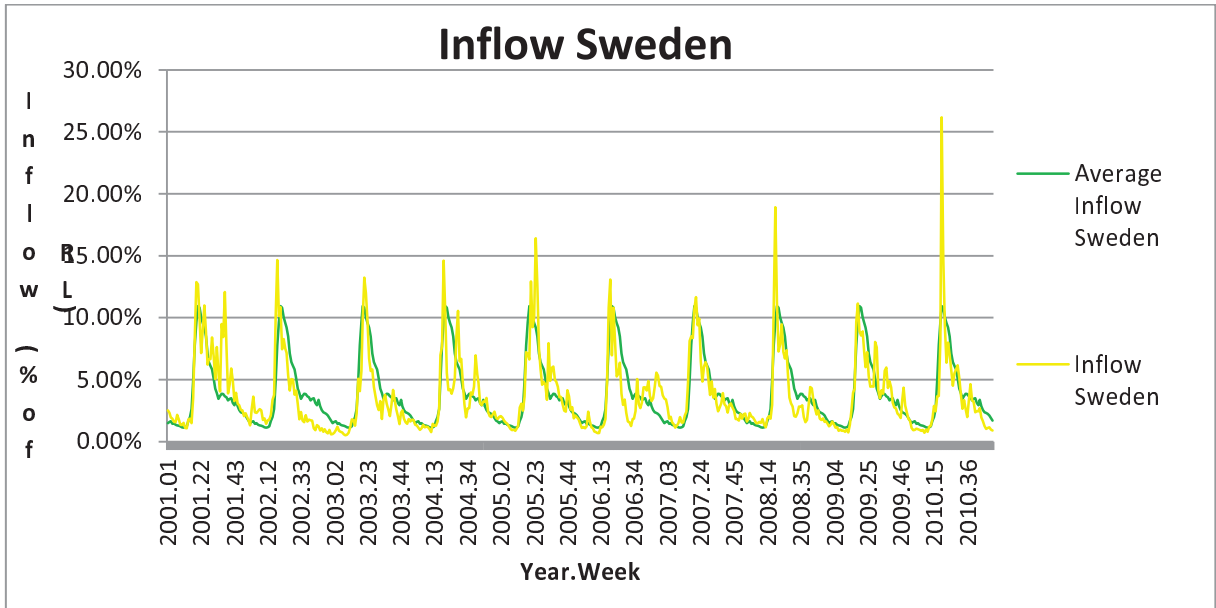


Figure 5: Actual and average inflow Sweden

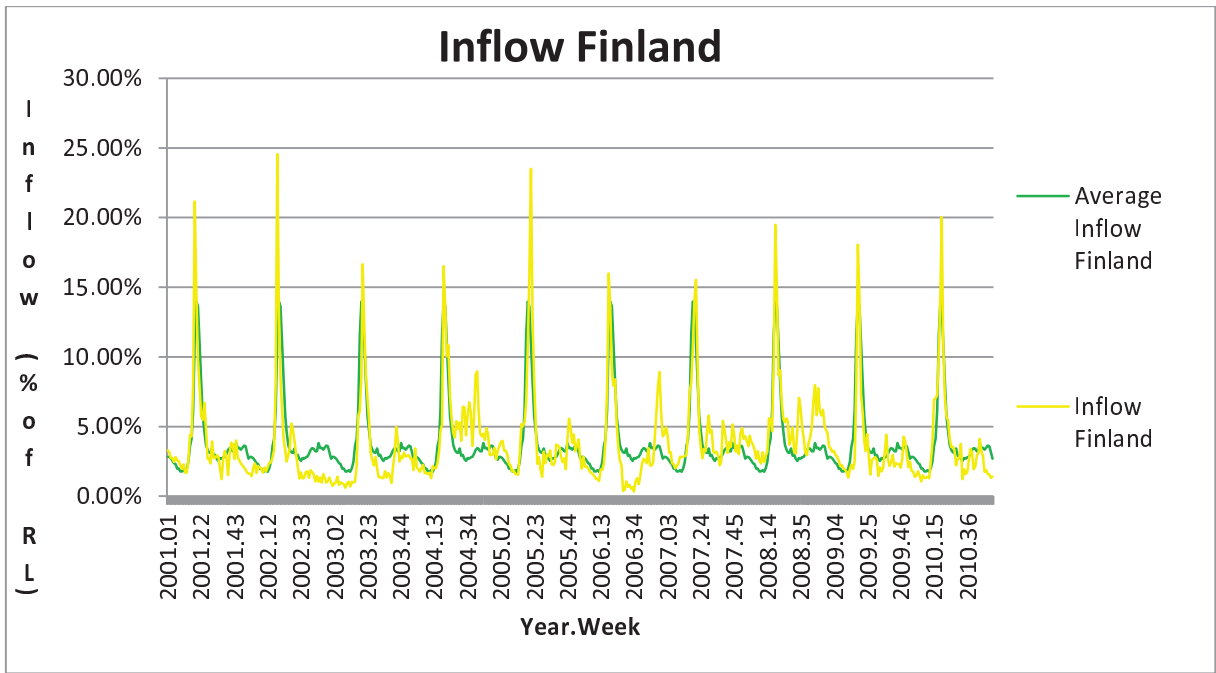


Figure 6: Actual and average inflow Finland

## Energy Equivalent of the Snow

The data for the energy equivalent of the snow is provided by the Norwegian Water Resources and Energy Directorate upon request (NVE 2011). The data states approximately how much energy (Gwh) can be produced from the snow that is stored in the mountains in connection to water reservoirs. We also have a season variable which is the average each week from 2001 through 2010. Note that this number tends to be exaggerated.

From figure seven we see that some years have lots of snow and some years have less snow. Note that the difference in energy equivalent also can come from difference in snow quality.

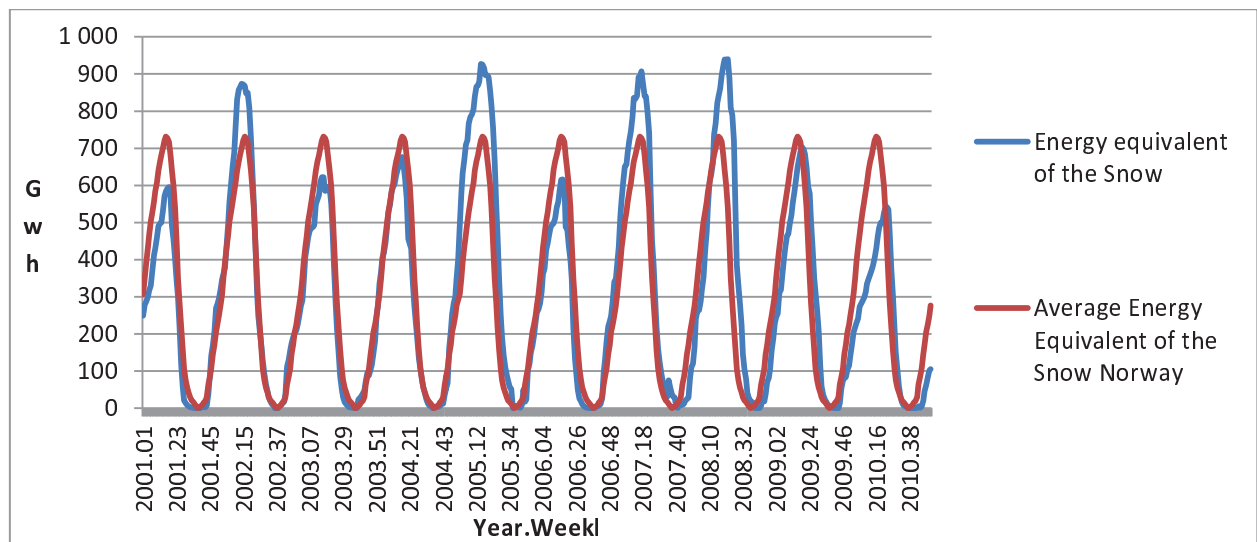


Figure 7: Energy Equivalent of the Snow in Norway

## Day

The daily future contracts were traded when Nord Pool was declared an official clearinghouse in 2001. In figure 8 we can see that the price are volatile, but seems to increase at a steady rate from 2001 to the middle of 2008. After this we get a shorter period with a large drop in prices. We should also notice that the last month of 2010 seems to be extreme with prices increasing drastically.

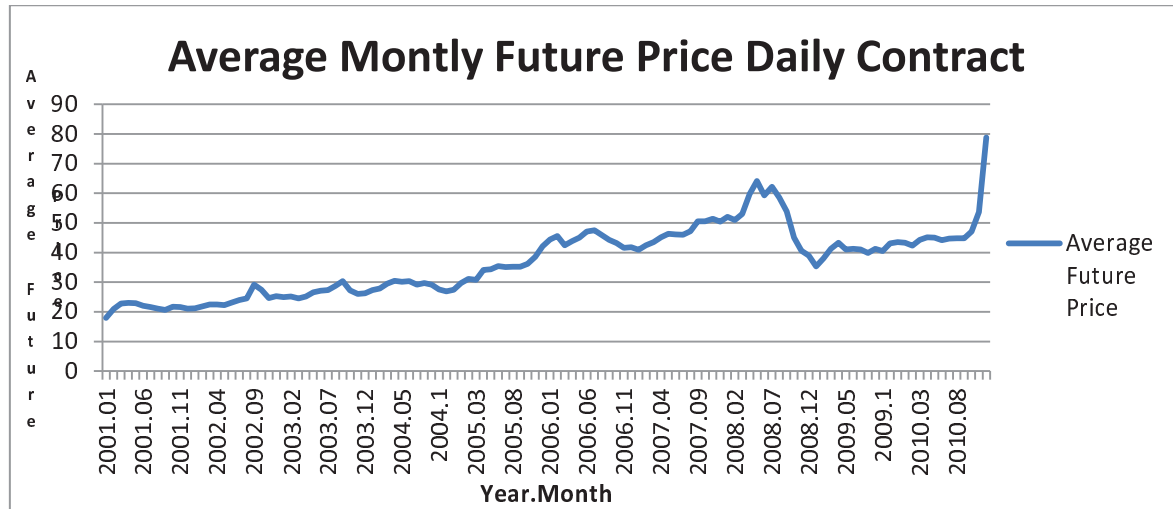


Figure 8: Average Monthly Future price for the Daily contract

At each time in our dataset we at least four weekly contracts traded. To make sure the dataset is balanced we have concentrated on the four contracts that are closest to maturity. This means that in the analysis we have included four observations each Wednesday from 2001 to 2010.

## Week

The weekly contracts were also traded when Nord Pool was declared an official clearinghouse in 2001. The weekly contracts are also volatile, but they have more extremes. From 2007 there are also high tops and low bottoms, but the price does not come back down to the level it had in 2007.

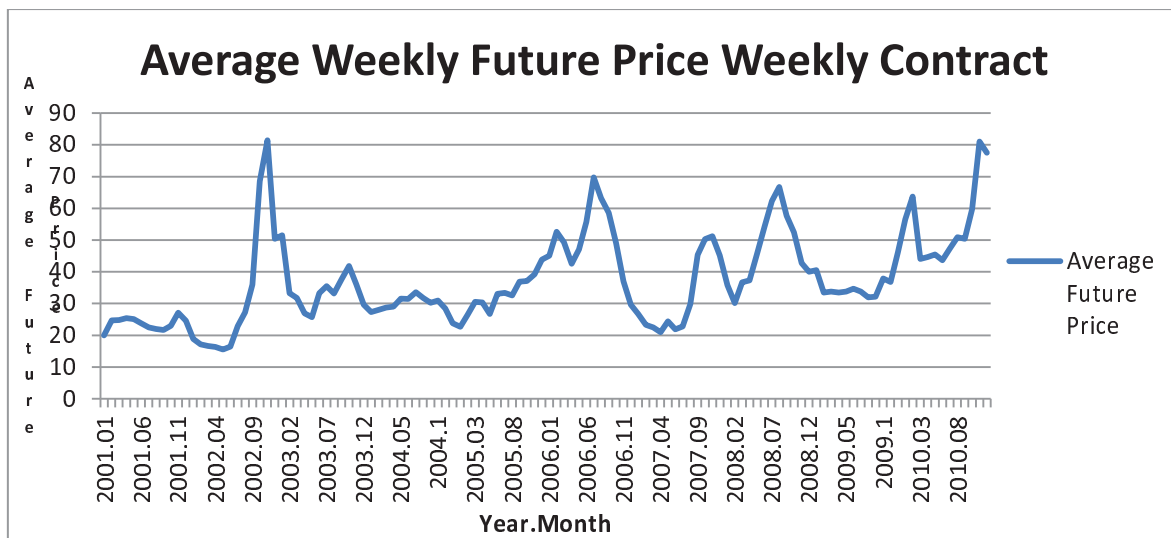


Figure 9: Average Monthly Future price for the Weekly contract

At each time in our dataset we have between four and eight weekly contracts traded. To make sure the dataset is balanced we have concentrated on the four contracts that are closest to maturity. This means that in the analysis we have included four observations each Wednesday from 2001 to 2010.

## Month

The monthly contracts were not introduced to the market before July 2003. These contracts seem less volatile from one period to another, and the increase at the end of the period looks like increases in previous periods.

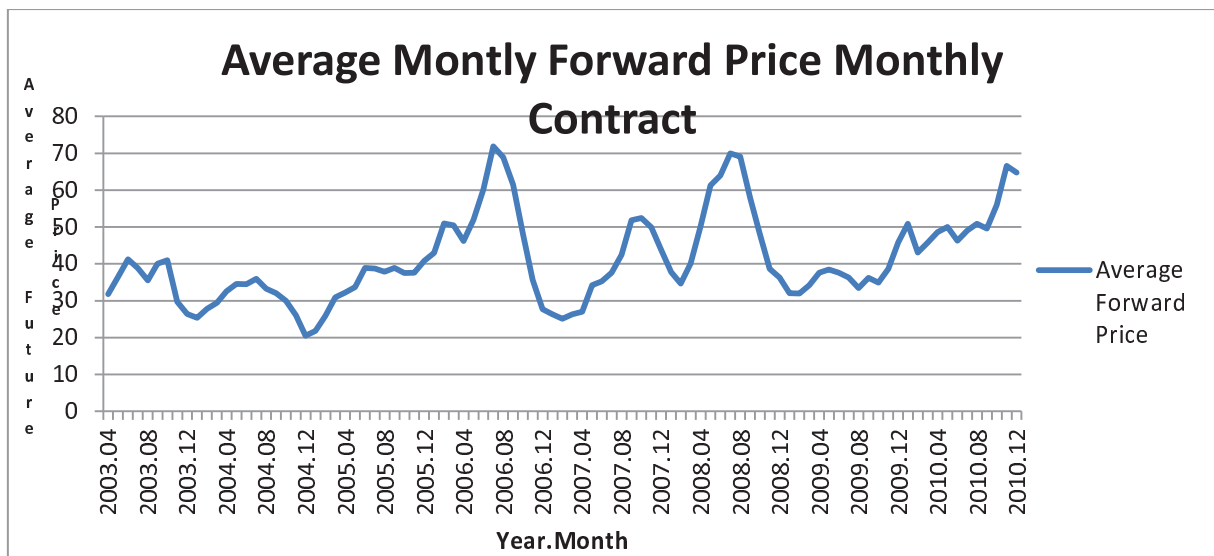


Figure 10: Average Monthly Future price for the Monthly contract

When the contracts were introduced there where fur contract traded at one time, but in September 2003 this increased to at least six contracts traded each day. In the analysis we have concentrated on the time from September 2003 to 2010, and we have used the six contracts closes to maturity.

## Quarter

The quarterly contracts, sometimes referred to seasonal contracts, were introduced to the market in 2004. Prices here increases over a longer period of time, decreases over a short period before increasing again.

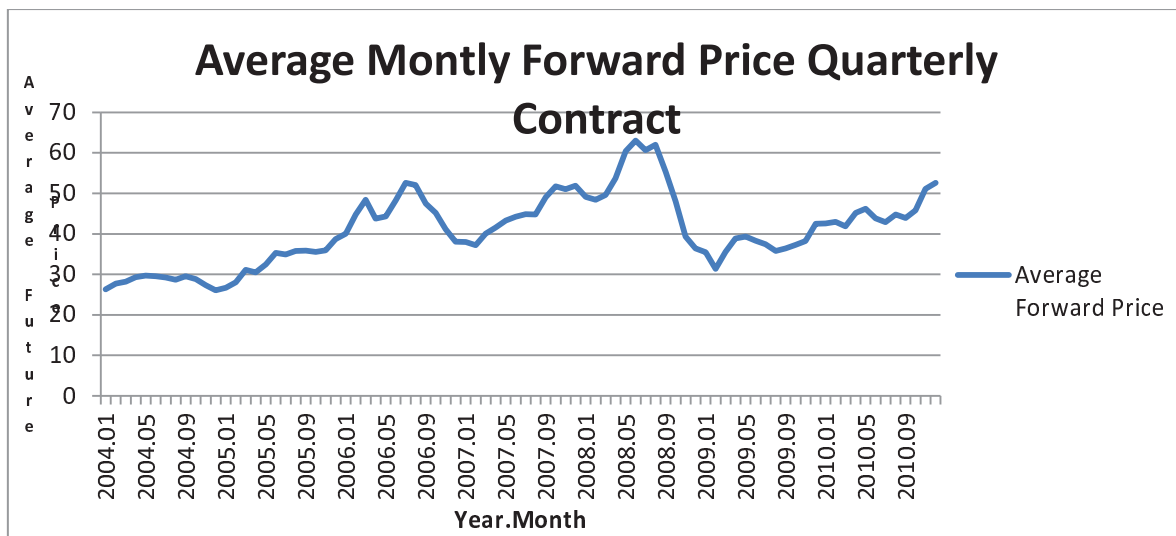


Figure 11: Average Monthly Future price for the Quarterly contract

When the contracts were introduced there were four contracts, but from 2005 this increased to eight contracts. In the analysis we have included the eight contracts traded each day from 2005 through 2010.



## Year

The yearly contracts were the first ones introduced in 1997, and was then traded when Nord Pool became an official clearinghouse in 2001. Except for one period with decreasing prices the average price for the monthly contracts seems to be increasing steadily.

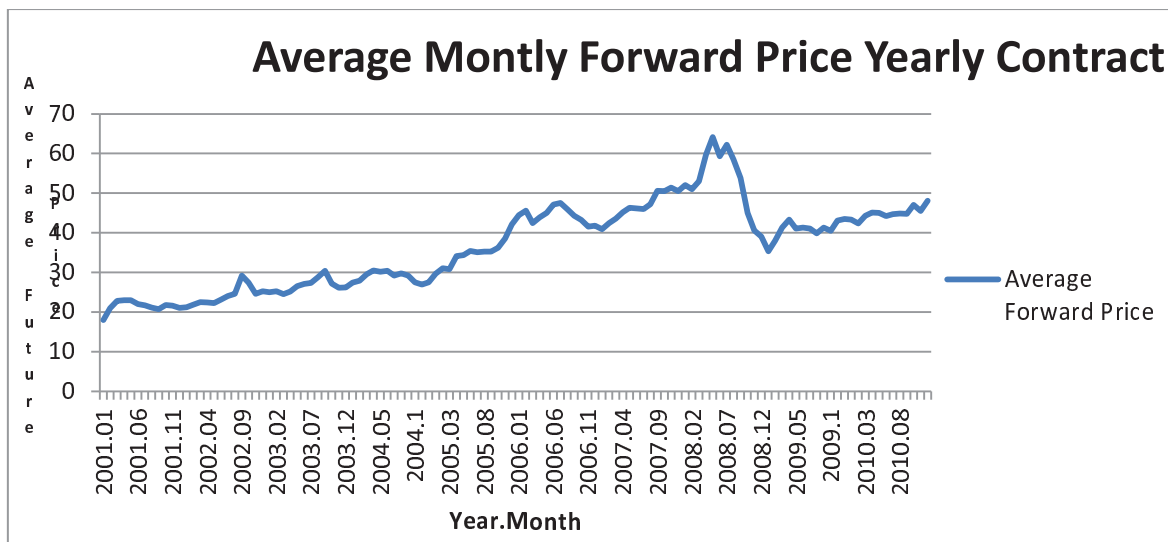


Figure 12: Average Monthly Future price for the Yearly contract

The yearly contracts initially had a three year time horizon, meaning there were three different yearly contracts traded at any given time. In 2006 the time horizon increased to six years, and thereby increasing the number of contracts traded at any given time. To keep the dataset balanced we have included the three contracts closest to maturity from 2001 through 2010.

## Chapter 5, Results

When constructing the model we have the variables mentioned above. In the estimation we have marked the variables with numbers:

*Name* – Name of contract ,  $ENOM + type + maturity\ point$

*Date* – Date of observation

*DTM* – Days to maturity ( $T$ )

*FP* – Price of contract (future or forward)

*SP* – Spot price

(1) *ARLN* – average reservoir level in Norway

(2) *RLN* – reservoir level in Norway

(3) *ARLS* – average reservoir level in Sweden

(4) *RLS* – reservoir level in Sweden

(5) *ARLF* – average reservoir level in Finland

(6) *RLF* – reservoir level in Finland

(7) *AIN* – average inflow in Norway

(8) *IN* – Inflow to reservoirs in Norway

(9) *AIS* – average inflow in Sweden

(10) *IS* – Inflow to reservoirs in Sweden

(11) *AIF* – average inflow in Finland

(12) *IF* – Inflow to reservoirs in Finland

(13) *AEESN* – Average Energy equivalent of the snow in Norway

(14) *EESN* – Energy equivalent of the snow in Norway

(15)  $RN = RLN - ARLN$

(16)  $RS = RLS - ARLS$

(17)  $RF = RLF - ARLF$

(18)  $IFN = IN - AIN$

(19)  $IFS = IS - AIS$

(20)  $IFF = IF - AIF$

(21)  $ESN = EESN - AEESN$

To be able to calculate for the effect caused by time to maturity (T), and the properties of convenience yield and alternative cost we have created three sets of variables used in the estimation:

$$x(n) = n * DTM$$

Last we created a variable that combined the future price and the spot price on the left side:

$$lnb = lns - lnf$$

## Day

All variables in the dataset are stationary, no variables has zero variance.

The models for the actual observations are all linear and do not have serial correlation at the 1% level. The explanatory power is greatest for the model which includes all hydro factors, even though it is low at 4,2%. The joint tests in this model show significance, but the individual tests show only reservoir level for Finland and snow are significant. The model for individual hydrological factors shows only reservoir level as individually significant.

The models for the seasonal variables also have functional forms that satisfy the time series assumptions at the 1% level. Again we see that the joint tests in the model including all hydrological factors show significance. The individual tests fail in three of four models, and it is only in the model for reservoir level where we find that Norway and Finland are individually significant. The overall explanatory power of the models is below 5%, and the model for snow does not have explanatory power.

The models which combine the actual observations with the seasonal variables also satisfy the functional form at the 1% level, but have they have an overall low explanatory power under 5%. In the model for all hydrological factors the joint test for actual observation and seasonal variables are significant. The actual observations and the seasonal variables for Norway and Sweden for inflow in all countries are also independently significant in this model. In the model for reservoir level actual observation and seasonal variable for Norway and the seasonal variable for Finland are significant, and the joint tests show significance. In the two other models we have neither individually or jointly significance.

The analysis for the models with difference variables shows that the model for inflow is not linear in its parameters. The model including all hydrological factors has joint significance for the variables, but neither in this model or in the others we have individual significance. More important none of the tests show explanatory power.

Last we have the models combining actual observations and difference variables. These have the same explanatory power as the models combining actual observation with seasonal variables. All models are linear, and none of them has a problem with serial correlation. The model including all hydrological factors has only the difference variable for inflow in Sweden as significant, but the joint tests show significance for the grouping of variables. The model for reservoir level has the actual observation for Finland and the difference variable for Norway and Finland as individually significant, and the joint test show significant in groupings. The model for inflow has no individually significant variables, but the actual observations are jointly significant.

## Week

All variables in the dataset are stationary.

The models for actual observations do not hold for the assumptions regarding the functional form. The model including all hydrological factors and the model for inflow are not linear in their parameters, and the models for the individual hydrological factors have all problems with serial correlation. Only the model for inflow has significant variables at the actual observed inflow for Norway are individually significant. In all other models we have neither individual nor joint significance. The explanatory power varies from 24,07% to 3,74%

The models for the seasonal variables have all problems with serial correlation. All the models, except for the model only including inflow, are linear in their parameters. The model including all hydrological factors has the seasonal variable for inflow in Norway and Sweden and the seasonal variable for snow as individually significant, and the joint test show significance for groups.

The models which combine the actual observations with the seasonal variables have an overall larger explanatory power. The model for reservoir level is not linear and this model and the model for snow has a problem with serial correlation. The model for all hydrological facts has the seasonal variable for inflow in Finland as individually significant and the groups for seasonal reservoir and inflow variables as jointly significant. In the model for reservoir level all groups are jointly significant, and the seasonal variables for Norway and Sweden are individually significant. The model for inflow has the seasonal variables as jointly significant and the actual observed inflow for Sweden as individually significant. The model for snow has the seasonal variable as significant.

The analysis for the models with difference variables shows that they are all linear in the parameters, but have an issue with serial correlation. The explanatory power is greatest for the model including all hydrological factors, and in this model we have joint significance. In the model for snow variables are individually significant.

Last we have the models combining actual observations and difference variables. Here we have serial correlation in the models including only one hydrological factor, and the model for reservoir level does is not linear in its parameters. Tests show joint significance in the model for inflow, and in model for snow the difference variable has individual significance. The model that includes all hydrological variables has an explanatory power of 40,12%, and tests show that the difference variables for reservoir level and the actual observations for inflow are jointly significant.

## Month

All variables in the dataset are stationary.

The models for the actual observations have either a problem with serial correlation or are not linear in their parameters. The explanatory power varies from 36,91 in the model for all hydrological factors to 2,42% in the model for snow. Also here there are few variables with individual significance, but we have joint significance in our tests.

The models for the seasonal variables are only linear when including all hydrological factors. This model has an explanatory power of 32,9%, and we have joint significance for all variables. The other models have either one or none individually significant variables.

None of the models which combine the actual observations with the seasonal variables are linear in their parameters. They have a higher fraction of individual significance, and the explanatory power reaches from 56,19% to 8,58%

The analysis for the models with difference variables shows that all models are linear, but they all have an issue with serial correlation. The models including one hydrological factor each have all or all but one variable individually significant, while the model combining all hydrological factors has the variables for reservoir level jointly significant. The explanatory variable varies from 25,64% to 3,11%

Last we have the models combining actual observations and difference variables. As with the models combining actual observations with seasonal variables they are not linear in their parameters, but the model combining all hydrological factors has an explanatory power over 50%. In this model the variables for difference in reservoir level and snow are individually significant, while the variables for difference in inflow are jointly significant.

## Quarter

All variables in the dataset are stationary.

The models for the actual observations do not have serial correlation. The models for all hydrological factors and for snow are not linear in their parameters, and the model for reservoir level does not have explanatory power. The model for inflow has a low explanatory power of 8,58%, and the inflow in Sweden is not individually significant.

The models for the seasonal variables do either lack linear parameters or explanatory power. The models for inflow and snow do not have significant variables, and in the model for reservoir Sweden is not significant. In the model including all hydrological factors the seasonal variables for inflow are individually significant, and all joint tests show significance.

The models which combine the actual observations with the seasonal variables lack linear parameters. The joint tests show significance, and the explanatory power is between 50% and 11%.

The analysis for the models with difference variables show that the model for all hydrological factors is linear, has an explanatory power of 43,02%, has individual significance in all variables except inflow for Finland, has joint significance, but has a problem with serial correlation. The model for reservoir level is also linear in its parameters and has an explanatory power of 40,60%, with only the difference for Finland as not individually significant, but also has an issue with serial correlation.

Last we have the models combining actual observations and difference variables. Again none of the models are linear. The explanatory power varies from 50,4% to 11,64%, but all the models have significant difference variables.

## Year

All variables in the dataset are stationary.

The models for the actual observations are linear in the parameters, but we have an issue with serial correlation for the models for reservoir level and snow. The explanatory powers are low, and all tests reject significant variables, both individually and significant.

The models for the seasonal variables are also linear, and only the model for snow has a problem with serial correlation. This model does not have explanatory power either. The other models have low explanatory powers, and all tests reject significant variables, both individually and significant.

The models which combine the actual observations with the seasonal variables do not have a problem with serial correlation. However the model for inflow is not linear in its parameters. All explanatory powers are above 17%, and the model including all hydrological factors has an explanatory power of 51%. Also here all tests reject significant variables, both individually and significant.

The analyses for the models with difference variables show no problem with serial correlation, but the models for reservoir level and inflow are not significant. Explanatory power varies from 43,66% to 13,63%, and all tests reject significant variables, both individually and significant.

Last we have the models combining actual observations and difference variables. Again we do not have an issue with serial correlation, but the model for inflow is not linear in its parameters. The explanatory powers are the same as for the models combining actual observations and seasonal variables. Again all tests reject significant variables, both individually and significant.



## Chapter 6, Discussion

So are the future and forward contract prices sensitive to the hydrological factors reservoir level, inflow and energy equivalent of the snow?

For the daily contracts the models has all over little explanatory power for the price effect not caused by the spot price. The models including all hydrological factors seem the best as we have joint significance for all groups. The fact that there is only joint significance and not individual significance suggests that we need to look at the total of the hydrological factors rather than dividing them into countries. The future and forward prices are prices for the whole Nord Pool area, so this makes sense. We get the largest explanatory power by combining the actual observations with either the seasonal variables or the difference variable, suggesting that that deviation from the normal drives the prices.

The models for the weekly contracts have a higher explanatory power than for the daily contracts, this might be because there is little uncertainty in the daily contracts regarding hydrological factors and therefore they don't drive the price in the same way as they do for the weekly contracts. Also for the weekly contracts we get the best results for the combined models, but which one we choose has something to say to what variables are jointly significant. However it seems that the variables for reservoir level and inflow are more significant as they are more often statistically significant both jointly and individually in our estimations. Both inflow and reservoir is easier to measure and easier to handle in estimations than the energy equivalent of the snow, which is often overrated.

The models do not have a good fit with the data for the monthly and quarterly contracts, but the fact that we have higher explanatory power and more significant variables both individually and jointly, suggest that they are an important factor in the price setting of the monthly forward contracts. The explanatory powers for all models including all hydrological factors are at least 25%, and they all have joint significance for either reservoir level, inflow or all, this follows with the reasoning for the weekly contract that reservoir level and inflow are easier to handle.

For the yearly contracts our models has a good fit where only four lacks linearity and only three has a problem with serial correlation. The explanatory power is also good for the models combining actual observations with the seasonal variables or difference variables, and the models for only seasonal variables. This again suggests that the deviation from the normal drives the prices. The big problem with the yearly contracts and our models however is the fact that no variables are statistically significant, not jointly nor individually. The yearly contracts has a long life span, and shifts from almost total uncertainty when the contract is first traded to almost total certainty when the contract is close to maturity. However most of the maturity time is in the time span with high uncertainty, and forecasting may very well have more effect on prices than actual observations. The higher explanatory power in our models does on the other hand suggest some effect from actual observations, making it possible that forecasting adjusted for actual observations is likely to drive prices.

There is also numerous other factors that has been uncovered in the analysis, but has not yet been mentioned. With some exceptions each group of models are arranged the same way when it comes to explanatory power. The model including all hydrological factors has the highest explanatory power, and then follows the model for reservoir level, before there is a jump down to the model for inflow and then last the model for snow. This can be reflected into the real world media where reservoir level is a high focus, the rain is a focus when we are hoping for low electricity prices, and snow is only a topic if reservoirs are low or there is so much snow that there is a probability of overflow.

Another factor which we have not calculated for in our models are the psychological factor. Traders use models to help them make decisions, but the models do not eliminate the human factor that is the qualities of the trader. The most important quality is how the trader feel about risk, where a risk seeking trader might have a greater chance of over paying, while a risk averse trader faces the threat of waiting too long and thereby lose money.

In our models we have not considered that we are analyzing a market with basic supply and demand. Our analysis does only look at the supply side, but the demand side does also affect the price. The analysis suggests that the demand side have different preferences than the input factors of hydro energy when they trade future and forward contracts. Included in the demand side are also speculators which trade the contracts purely with the intention of making money. They of course base their trading diction on the factors analyzed above, but might be more open to factors not associated with production as there is no physical delivery.

The last important factor excluded in our analysis is the risk premium. All participants run a risk when conduction trades with the future and forward contracts. If one participant earns on the deal, it follows that the counterpart loses the same amount. Which part pays a risk premium is not easily analyzed, and it may very well shift over time as there is a danger of overflow or a danger of low reservoir levels.

## Chapter 7, Conclusion

The models analyzed in this paper do not create a good enough picture of what drives the future and forward prices at Nord Pool. The hydrological factors are a part of the picture that makes up the price of future and forward contracts at Nord Pool. However they are not the entire picture, and they affect different contracts with different timespans to various degrees:

- The daily contract has a short time span, so the uncertainty that separates the future price from the spot price is not determined by observed hydrological factors.
- The weekly, monthly and quarterly contracts have most of their trading periods in a middle time span period where the hydrological factors, in combination with other aspects of the supply and demand market, is a part of the uncertainty. This means that the hydrological factors are affecting the prices in some way.
- The yearly contracts have most of their trading periods at a long time span, and this makes the uncertainty high. It also means that the actual observations of hydrological factors today are not that important when trying to price this uncertainty.

The analysis also strongly suggests that the different hydrological factors affect the prices in various degrees. However it is clear that the joint observations for all countries have more effect than each observation alone. The findings of the individual hydrological factors are:

- Reservoir level alone has higher explanatory power than inflow and snow
- Inflow has higher explanatory power than snow
- The observations for inflow and reservoir level are more often significant in pricing future and forward contracts.

When we see this in the light of the initial hypothesis we see that the short term hydrological balance of reservoir, inflow and snow are not good measurements for the adjustment made to the spot price to get the future and forward prices.

- An increase in reservoir level affects prices
- A high inflow of water affects prices
- There is probably a minimal or no effect of snow in the mountains on the future- and forward prices.
- Different contracts with different time aspects are affected differently by the hydrological factors. They are all affected by the joint hydrological factors in the area, but it is mostly for the three contracts with middle time span.

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## Appendix A, Stata Results

### Day

```
. xtfisher lnb, lags(5)
```

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

```
chi2(8) = 275.0117
Prob > chi2 = 0.0000
```

```
. xtfisher x1, lags(5)
```

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

```
chi2(8) = 472.6370
Prob > chi2 = 0.0000
```

```
. xtfisher x2, lags(5)
```

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

```
chi2(8) = 495.5321
Prob > chi2 = 0.0000
```

```
. xtfisher x3, lags(5)
```

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

```
chi2(8) = 449.1002
Prob > chi2 = 0.0000
```

```
. xtfisher x4, lags(5)
```

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

```
chi2(8) = 451.8426
Prob > chi2 = 0.0000
```

```
. xtfisher x5, lags(5)
```

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

```
chi2(8) = 372.9032
Prob > chi2 = 0.0000
```

```
. xtfisher x6, lags(5)
```

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

```
chi2(8) = 381.4165
Prob > chi2 = 0.0000
```

. xtfisher x7, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(8) = 397.6871  
Prob > chi2 = 0.0000

. xtfisher x8, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(8) = 375.1684  
Prob > chi2 = 0.0000

. xtfisher x9, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(8) = 370.1892  
Prob > chi2 = 0.0000

. xtfisher x10, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(8) = 358.8293  
Prob > chi2 = 0.0000

. xtfisher x11, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(8) = 370.8051  
Prob > chi2 = 0.0000

. xtfisher x12, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(8) = 377.8199  
Prob > chi2 = 0.0000

. xtfisher x13, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(8) = 493.9675  
Prob > chi2 = 0.0000

. xtfisher x14, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(8) = 505.7895  
Prob > chi2 = 0.0000

. xtfisher x15, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(8) = 301.0535  
Prob > chi2 = 0.0000

. xtfisher x16, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(8) = 284.7813  
Prob > chi2 = 0.0000

. xtfisher x17, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(8) = 259.1397  
Prob > chi2 = 0.0000

. xtfisher x18, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(8) = 223.5178  
Prob > chi2 = 0.0000

. xtfisher x19, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(8) = 220.3725  
Prob > chi2 = 0.0000

. xtfisher x20, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(8) = 299.1259  
Prob > chi2 = 0.0000

. xtfisher x21, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(8) = 246.2229  
Prob > chi2 = 0.0000

```
. *1 test actual variables
```

```
. reg lnb x2 x4 x6 x8 x10 x12 x14,robust cluster(PD)
```

Linear regression

Number of obs = **2048**  
 F( 2, 3) = .  
 Prob > F = .  
 R-squared = **0.0420**  
 Root MSE = **.19155**

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	.0116457	.0137063	0.85	0.458	-.0319739	.0552653
x4	.0103048	.0125141	0.82	0.471	-.0295208	.0501303
x6	-.0474883	.0044418	-10.69	0.002	-.0616241	-.0333525
x8	-.1399921	.0750032	-1.87	0.159	-.3786857	.0987014
x10	-.1202128	.026695	-4.50	0.020	-.2051682	-.0352575
x12	.0281882	.0152689	1.85	0.162	-.0204043	.0767807
x14	-.0000145	9.87e-07	-14.74	0.001	-.0000177	-.0000114
_cons	.0329395	.0019571	16.83	0.000	.0267113	.0391678

```
. test x2 x4 x6
```

- ( 1) x2 = 0
- ( 2) x4 = 0
- ( 3) x6 = 0

F( 3, 3) = **3771.13**  
 Prob > F = **0.0000**

```
. test x8 x10 x12
```

- ( 1) x8 = 0
- ( 2) x10 = 0
- ( 3) x12 = 0

F( 3, 3) = **48.70**  
 Prob > F = **0.0048**

```
. predict u,r
```

```
. predict yhat,xb
```

```
. reg lnb x2 x4 x6 x8 x10 x12 x14 l.u,robust cluster(PD)
```

Linear regression

Number of obs = **2044**  
 F( 2, 3) = .  
 Prob > F = .  
 R-squared = **0.0422**  
 Root MSE = **.19175**

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	.0114696	.0140877	0.81	0.475	-.0333636	.0563029
x4	.0105443	.0129781	0.81	0.476	-.0307578	.0518463
x6	-.0475927	.0044269	-10.75	0.002	-.0616809	-.0335044
x8	-.1382922	.0754479	-1.83	0.164	-.3784009	.1018166
x10	-.1219139	.0267795	-4.55	0.020	-.2071381	-.0366896
x12	.0279296	.0157231	1.78	0.174	-.0221084	.0779675
x14	-.0000144	9.60e-07	-15.00	0.001	-.0000175	-.0000113
u						
l1.	-.0176454	.0045386	-3.89	0.030	-.0320891	-.0032017
_cons	.0329214	.0020231	16.27	0.001	.026483	.0393599



```

. gen y2=yhat*yhat
.
. gen y3=y2*yhat
.
. reg lnb x2 x4 x6 x8 x10 x12 x14 y2 y3, robust cluster(PD)
Linear regression                               Number of obs =    2048
                                                F( 2, 3) = .
                                                Prob > F = .
                                                R-squared = 0.0420
                                                Root MSE = 0.19164

```

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	.0098937	.0069385	1.43	0.249	-.0121877	.0319751
x4	.0097327	.0147404	0.66	0.556	-.0371778	.0566432
x6	-.0442399	.0114966	-3.85	0.031	-.0808273	-.0076524
x8	-.1266912	.1296074	-0.98	0.400	-.5391598	.2857773
x10	-.1073766	.025515	-4.21	0.025	-.1885768	-.0261765
x12	.0261177	.0172801	1.51	0.228	-.0288753	.0811107
x14	-.0000137	4.37e-06	-3.13	0.052	-.0000276	2.14e-07
y2	-.7823772	3.922551	-0.20	0.855	-13.26568	11.70093
y3	-1.200107	11.30839	-0.11	0.922	-37.18844	34.78823
_cons	.0308836	.0104892	2.94	0.060	-.0024977	.0642648

```

. test y2 y3
( 1) y2 = 0
( 2) y3 = 0
      F( 2, 3) = 0.07
      Prob > F = 0.9317

```

```
. *2 test actual variables reservoir level
```

```
. reg lnb x2 x4 x6,robust cluster(PD)
```

Linear regression

```
Number of obs = 2048
F( 2, 3) = .
Prob > F = .
R-squared = 0.0340
Root MSE = .19215
```

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	.0436548	.0113139	3.86	0.031	-.0076489	.0796606
x4	.0142799	.0122518	1.17	0.328	-.0247109	.0532706
x6	-.0993116	.0037849	-26.24	0.000	-.111357	-.0872663
_cons	.0242586	.0073516	3.30	0.046	.0008625	.0476546

```
. predict u2,r
```

```
. predict y2hat,xb
```

```
. reg lnb x2 x4 x6 l.u2,robust cluster(PD)
```

Linear regression

```
Number of obs = 2044
F( 2, 3) = .
Prob > F = .
R-squared = 0.0343
Root MSE = .19235
```

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	.0440387	.0115847	3.80	0.032	-.0071711	.0809063
x4	.0142328	.0124954	1.14	0.337	-.0255331	.0539988
x6	-.099796	.0037661	-26.50	0.000	-.1117813	-.0878107
u2	-.0179147	.0060982	-2.94	0.061	-.0373218	.0014923
_cons	.0243975	.007385	3.30	0.046	.000895	.0479

```
. gen y22=y2hat*y2hat
```

```
. gen y23=y22*y2hat
```

```
. reg lnb x2 x4 x6 y22 y23, robust cluster(PD)
```

Linear regression

```
Number of obs = 2048
F( 2, 3) = .
Prob > F = .
R-squared = 0.0342
Root MSE = .19223
```

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	.0497726	.0308582	1.61	0.205	-.0484318	.1479771
x4	.0167199	.0076215	2.19	0.116	-.0075351	.040975
x6	-.1146175	.0380676	-3.01	0.057	-.2357655	.0065306
y22	5.179177	8.873185	0.58	0.600	-23.05926	33.41761
y23	32.2015	44.3388	0.73	0.520	-108.9043	173.3073
_cons	.028089	.0041539	6.76	0.007	.0148695	.0413085

```
. test y22 y23
```

```
( 1) y22 = 0
( 2) y23 = 0
```

```
F( 2, 3) = 1.82
Prob > F = 0.3039
```

. \*3 test actual variables inflow

. reg lnb x8 x10 x12,robust cluster(PD)

Linear regression Number of obs = 2048  
F( 2, 3) = .  
Prob > F = .  
R-squared = 0.0324  
Root MSE = .19231

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x8	<b>-.2596316</b>	<b>.0944342</b>	<b>-2.75</b>	<b>0.071</b>	<b>-.5601632</b>	<b>.0409001</b>
x10	<b>-.0910497</b>	<b>.0483498</b>	<b>-1.88</b>	<b>0.156</b>	<b>-.2449205</b>	<b>.062821</b>
x12	<b>-.1247585</b>	<b>.0309809</b>	<b>-4.03</b>	<b>0.028</b>	<b>-.2233535</b>	<b>-.0261634</b>
_cons	<b>.0051515</b>	<b>.012892</b>	<b>0.40</b>	<b>0.716</b>	<b>-.0358765</b>	<b>.0461795</b>

. predict u3, r

. predict y3hat,xb

. reg lnb x8 x10 x12 l.u3,robust cluster(PD)

Linear regression Number of obs = 2044  
F( 2, 3) = .  
Prob > F = .  
R-squared = 0.0325  
Root MSE = .19253

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x8	<b>-.2591145</b>	<b>.0954674</b>	<b>-2.71</b>	<b>0.073</b>	<b>-.5629346</b>	<b>.0447055</b>
x10	<b>-.0916119</b>	<b>.0487682</b>	<b>-1.88</b>	<b>0.157</b>	<b>-.2468142</b>	<b>.0635904</b>
x12	<b>-.1254656</b>	<b>.0313388</b>	<b>-4.00</b>	<b>0.028</b>	<b>-.2251998</b>	<b>-.0257314</b>
u3						
L1.	<b>-.0131504</b>	<b>.0026466</b>	<b>-4.97</b>	<b>0.016</b>	<b>-.0215732</b>	<b>-.0047277</b>
_cons	<b>.0051943</b>	<b>.0130507</b>	<b>0.40</b>	<b>0.717</b>	<b>-.0363388</b>	<b>.0467273</b>

. gen y32=y3hat\*y3hat

. gen y33=y32\*y3hat

. reg lnb x8 x10 x12 y32 y33, robust cluster(PD)

Linear regression Number of obs = 2048  
F( 2, 3) = .  
Prob > F = .  
R-squared = 0.0332  
Root MSE = .19233

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x8	<b>-.1826418</b>	<b>.2450945</b>	<b>-0.75</b>	<b>0.510</b>	<b>-.962642</b>	<b>.5973584</b>
x10	<b>-.1062632</b>	<b>.0339238</b>	<b>-3.13</b>	<b>0.052</b>	<b>-.2142237</b>	<b>.0016974</b>
x12	<b>-.1075376</b>	<b>.1135344</b>	<b>-0.95</b>	<b>0.413</b>	<b>-.4688549</b>	<b>.2537797</b>
y32	<b>-4.009901</b>	<b>7.941731</b>	<b>-0.50</b>	<b>0.648</b>	<b>-29.28403</b>	<b>21.26423</b>
y33	<b>-19.0522</b>	<b>20.79003</b>	<b>-0.92</b>	<b>0.427</b>	<b>-85.21536</b>	<b>47.11096</b>
_cons	<b>.0041574</b>	<b>.0239808</b>	<b>0.17</b>	<b>0.873</b>	<b>-.0721603</b>	<b>.0804751</b>

. test y32 y33

( 1) **y32 = 0**

( 2) **y33 = 0**

F( 2, 3) = **9.84**  
Prob > F = **0.0481**

. \*4 test actual variables snow

. reg lnb x14,robust cluster(PD)

Linear regression

Number of obs = 2048  
 F( 1, 3) = 13.32  
 Prob > F = 0.0355  
 R-squared = 0.0118  
 Root MSE = .19426

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x14	-.0000252	6.89e-06	-3.65	0.035	-.0000471	-3.22e-06
_cons	-.014467	.0175305	-0.83	0.470	-.0702569	.0413229

. predict u4,r

. predict y4hat,xb

. reg lnb x14 l.u4,robust cluster(PD)

Linear regression

Number of obs = 2044  
 F( 2, 3) = 187.29  
 Prob > F = 0.0007  
 R-squared = 0.0120  
 Root MSE = .19446

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x14	-.0000253	6.59e-06	-3.85	0.031	-.0000463	-4.37e-06
u4	.0133086	.0189105	0.70	0.532	-.0468729	.0734901
_cons	-.0144188	.0171228	-0.84	0.462	-.0689111	.0400735

. gen y42=y4hat\*y4hat

. gen y43=y42\*y4hat

. reg lnb x14 y42 y43, robust cluster(PD)

Linear regression

Number of obs = 2048  
 F( 2, 3) = .  
 Prob > F = .  
 R-squared = 0.0127  
 Root MSE = .19426

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x14	.0000362	.0000524	0.69	0.539	-.0001305	.0002029
y42	-43.20927	52.02538	-0.83	0.467	-208.7772	122.3587
y43	-207.3436	325.7551	-0.64	0.570	-1244.042	829.3544
_cons	-.0129468	.0246301	-0.53	0.636	-.0913307	.0654372

. test y42 y43

( 1) y42 = 0  
 ( 2) y43 = 0

F( 2, 3) = 4.14  
 Prob > F = 0.1372

. \*5 Test all seasonal variables

. reg lnb x1 x3 x5 x7 x9 x11 x13,robust cluster(PD)

Linear regression

Number of obs =	2048
F( 2, 3) =	.
Prob > F =	.
R-squared =	0.0430
Root MSE =	.19145

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	.4635669	.2953406	1.57	0.215	-.4763386	1.403472
x3	-.7841599	.5597514	-1.40	0.256	-2.565539	.9972189
x5	.3130138	.2760936	1.13	0.339	-.5656392	1.191667
x7	-.6223248	.1533543	-4.06	0.027	-1.110367	-.134283
x9	.6172207	.2189299	2.82	0.067	-.0795118	1.313953
x11	-.4639507	.1590289	-2.92	0.062	-.9700517	.0421503
x13	-.0001697	.0001171	-1.45	0.243	-.0005424	.000203
_cons	.0322026	.0050203	6.41	0.008	.0162257	.0481795

. test x1 x3 x5

- ( 1) x1 = 0
- ( 2) x3 = 0
- ( 3) x5 = 0

F( 3, 3) = 147.35  
 Prob > F = 0.0009

. test x7 x9 x11

- ( 1) x7 = 0
- ( 2) x9 = 0
- ( 3) x11 = 0

F( 3, 3) = 207.15  
 Prob > F = 0.0006

. predict u5,r

. predict y5hat,xb

. reg lnb x1 x3 x5 x7 x9 x11 x13 l.u5,robust cluster(PD)

Linear regression

Number of obs =	2044
F( 2, 3) =	.
Prob > F =	.
R-squared =	0.0433
Root MSE =	.19164

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	.4579341	.3022521	1.52	0.227	-.5039668	1.419835
x3	-.774197	.5726637	-1.35	0.269	-2.596669	1.048275
x5	.3085132	.2823554	1.09	0.354	-.5900679	1.207094
x7	-.6195196	.1554315	-3.99	0.028	-1.114172	-.1248672
x9	.6119133	.2227595	2.75	0.071	-.0970068	1.320833
x11	-.4609145	.1628273	-2.83	0.066	-.9791038	.0572747
x13	-.0001677	.0001197	-1.40	0.256	-.0005487	.0002134
u5						
L1.	-.0189344	.004538	-4.17	0.025	-.0333762	-.0044925
_cons	.0322088	.0051116	6.30	0.008	.0159413	.0484763

```

. gen y52=y5hat*y5hat
.
. gen y53=y52*y5hat
.
. reg lnb x1 x3 x5 x7 x9 x11 x13 y52 y53, robust cluster(PD)
Linear regression                               Number of obs =    2048
                                                F( 2,          3) =    .
                                                Prob > F       =    .
                                                R-squared     =    0.0469
                                                Root MSE     =    .19114

```

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	1.063889	.488694	2.18	0.118	-.4913535	2.619131
x3	-1.750188	.8601746	-2.03	0.135	-4.487647	.9872712
x5	.675145	.3836616	1.76	0.177	-.5458375	1.896127
x7	-1.64401	.5561056	-2.96	0.060	-3.413787	.1257659
x9	1.608112	.5992049	2.68	0.075	-.298825	3.51505
x11	-1.119688	.3981802	-2.81	0.067	-2.386876	.1474987
x13	-.0003724	.0001794	-2.08	0.130	-.0009433	.0001985
y52	24.03265	11.98012	2.01	0.139	-14.09343	62.15873
y53	100.3879	55.59554	1.81	0.169	-76.54187	277.3178
_cons	.0637728	.0087188	7.31	0.005	.0360258	.0915197

```

. test y52 y53
( 1) y52 = 0
( 2) y53 = 0
      F( 2,          3) =    2.93
      Prob > F =    0.1968

```

. \*6 Test all seasonal variables reservoir level

. reg lnb x1 x3 x5,robust cluster(PD)

Linear regression Number of obs = 2048  
F( 2, 3) = .  
Prob > F = .  
R-squared = 0.0359  
Root MSE = .19196

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	.0554501	.0087585	6.33	0.008	.0275765	.0833237
x3	.037024	.0082052	4.51	0.020	.0109113	.0631367
x5	-.1346671	.0033146	-40.63	0.000	-.1452158	-.1241184
_cons	.0293607	.0053181	5.52	0.012	.0124361	.0462853

. predict u6,r

. predict y6hat,xb

. reg lnb x1 x3 x5 l.u6,robust cluster(PD)

Linear regression Number of obs = 2044  
F( 2, 3) = .  
Prob > F = .  
R-squared = 0.0363  
Root MSE = .19215

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	.0557126	.0088478	6.30	0.008	.027555	.0838701
x3	.0369322	.0082995	4.45	0.021	.0105196	.0633448
x5	-.1349596	.003341	-40.39	0.000	-.1455923	-.1243268
u6						
l1.	-.0184328	.0066308	-2.78	0.069	-.039535	.0026695
_cons	.0294378	.0053513	5.50	0.012	.0124076	.046468

. gen y62=y6hat\*y6hat

. gen y63=y62\*y6hat

. reg lnb x1 x3 x5 y62 y63, robust cluster(PD)

Linear regression Number of obs = 2048  
F( 3, 3) = .  
Prob > F = .  
R-squared = 0.0359  
Root MSE = .19206

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	.0531134	.0206226	2.58	0.082	-.0125169	.1187437
x3	.0366636	.0068217	5.37	0.013	.014954	.0583733
x5	-.1309371	.0262129	-5.00	0.015	-.2143582	-.0475161
y62	-.4877348	4.058743	-0.12	0.912	-13.40447	12.429
y63	-2.010623	19.07844	-0.11	0.923	-62.72673	58.70548
_cons	.0286837	.0022434	12.79	0.001	.0215443	.0358231

. test y62 y63

( 1) y62 = 0  
( 2) y63 = 0

F( 2, 3) = 0.01  
Prob > F = 0.9891

. \*7 Test all seasonal variables inflow

. reg lnb x7 x9 x11,robust cluster(PD)

Linear regression

Number of obs = 2048  
 F( 2, 3) = .  
 Prob > F = .  
 R-squared = 0.0380  
 Root MSE = .19176

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x7	-.6533859	.2209367	-2.96	0.060	-1.356505	.0497334
x9	.2854705	.1735839	1.64	0.199	-.2669511	.837892
x11	-.3234885	.0797107	-4.06	0.027	-.5771635	-.0698135
_cons	.0164823	.0110718	1.49	0.233	-.0187532	.0517178

. predict u7,r

. predict y7hat,xb

. reg lnb x7 x9 x11 l.u7,robust cluster(PD)

Linear regression

Number of obs = 2044  
 F( 2, 3) = .  
 Prob > F = .  
 R-squared = 0.0382  
 Root MSE = .19196

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x7	-.6561085	.2219137	-2.96	0.060	-1.362337	.05012
x9	.2889833	.1737028	1.66	0.195	-.2638166	.8417831
x11	-.3262818	.0798702	-4.09	0.027	-.5804645	-.0720991
u7	-.0183898	.0054089	-3.40	0.042	-.0356034	-.0011761
_cons	.0165706	.0112097	1.48	0.236	-.0191037	.0522448

. gen y72=y7hat\*y7hat

. gen y73=y72\*y7hat

. reg lnb x7 x9 x11 y72 y73, robust cluster(PD)

Linear regression

Number of obs = 2048  
 F( 2, 3) = .  
 Prob > F = .  
 R-squared = 0.0390  
 Root MSE = .19175

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x7	-.9972465	.2662034	-3.75	0.033	-1.844424	-.1500685
x9	.3222031	.0838313	3.84	0.031	.0554145	.5889916
x11	-.4926052	.1256565	-3.92	0.030	-.8925001	-.0927102
y72	14.25371	6.782641	2.10	0.126	-7.331684	35.8391
y73	59.13561	25.65205	2.31	0.104	-22.50066	140.7719
_cons	.0331869	.0158879	2.09	0.128	-.0173754	.0837492

. test y72 y73

- ( 1) y72 = 0
- ( 2) y73 = 0

F( 2, 3) = 3.94  
 Prob > F = 0.1450



. \*8 Test all seasonal variables snow

. reg lnb x13,robust cluster(PD)

Linear regression

Number of obs =	2048
F( 1, 3) =	10.30
Prob > F =	0.0490
R-squared =	0.0093
Root MSE =	.1945

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x13	-.0000238	7.41e-06	-3.21	0.049	-.0000473	-1.95e-07
_cons	-.0155208	.0180418	-0.86	0.453	-.0729378	.0418962

. predict u8,r

. predict y8hat,xb

. reg lnb x13 l.u8,robust cluster(PD)

Linear regression

Number of obs =	2044
F( 2, 3) =	220.39
Prob > F =	0.0006
R-squared =	0.0095
Root MSE =	.1947

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x13	-.000024	7.10e-06	-3.38	0.043	-.0000466	-1.38e-06
u8	.0126261	.0180265	0.70	0.534	-.0447424	.0699945
_cons	-.0154601	.0176308	-0.88	0.445	-.0715692	.0406489

. gen y82=y8hat\*y8hat

. gen y83=y82\*y8hat

. reg lnb x13 y82 y83, robust cluster(PD)

Linear regression

Number of obs =	2048
F( 2, 3) =	.
Prob > F =	.
R-squared =	0.0106
Root MSE =	.19447

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x13	.0001257	.0000895	1.40	0.255	-.000159	.0004103
y82	-146.3027	99.41384	-1.47	0.237	-462.6819	170.0765
y83	-995.317	707.5558	-1.41	0.254	-3247.075	1256.441
_cons	.0073601	.0343149	0.21	0.844	-.1018452	.1165655

. test y82 y83

( 1) y82 = 0  
( 2) y83 = 0

F( 2, 3) =	1.44
Prob > F =	0.3637

. \*9 test all actual and season variables

. reg lnb x1 x2 x3 x4 x5 x6 x7 x8 x9 x10 x11 x12 x13 x14,robust cluster(PD)

Linear regression

Number of obs =	2048
F( 2, 3) =	.
Prob > F =	.
R-squared =	0.0484
Root MSE =	.19123

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	.5282377	.2642387	2.00	0.139	-.3126878	1.369163
x2	-.0064145	.001846	-3.47	0.040	-.0122894	-.0005396
x3	-.8871857	.5253589	-1.69	0.190	-2.559112	.7847406
x4	.0178713	.0161945	1.10	0.350	-.0336668	.0694094
x5	.3880064	.2560209	1.52	0.227	-.4267664	1.202779
x6	-.051921	.0023516	-22.08	0.000	-.0594047	-.0444373
x7	-.7727594	.1044266	-7.40	0.005	-1.105091	-.4404275
x8	.0891649	.0481679	1.85	0.161	-.0641269	.2424568
x9	.8136472	.1313369	6.20	0.008	.3956746	1.23162
x10	-.0906862	.0472973	-1.92	0.151	-.2412073	.0598349
x11	-.6420141	.1404801	-4.57	0.020	-1.089084	-.1949438
x12	.1462873	.0069089	21.17	0.000	.1243	.1682747
x13	-.0001536	.0000978	-1.57	0.214	-.0004647	.0001575
x14	-.0000314	.0000115	-2.72	0.072	-.000068	5.31e-06
_cons	.0322538	.004978	6.48	0.007	.0164117	.0480959

. test x1 x2 x3 x4 x5 x6

( 1) x1 = 0  
 ( 2) x2 = 0  
 ( 3) x3 = 0  
 ( 4) x4 = 0  
 ( 5) x5 = 0  
 ( 6) x6 = 0  
 Constraint 1 dropped  
 Constraint 2 dropped  
 Constraint 6 dropped  
 F( 3, 3) = 15.98  
 Prob > F = 0.0238

. test x1 x3 x5

( 1) x1 = 0  
 ( 2) x3 = 0  
 ( 3) x5 = 0  
 F( 3, 3) = 214.68  
 Prob > F = 0.0005

. test x2 x3 x5

( 1) x2 = 0  
 ( 2) x3 = 0  
 ( 3) x5 = 0  
 F( 3, 3) = 65.19  
 Prob > F = 0.0031

. test x7 x8 x9 x10 x11 x12

( 1) x7 = 0  
 ( 2) x8 = 0  
 ( 3) x9 = 0  
 ( 4) x10 = 0  
 ( 5) x11 = 0  
 ( 6) x12 = 0  
 Constraint 2 dropped  
 Constraint 4 dropped  
 Constraint 6 dropped  
 F( 3, 3) = 24.62  
 Prob > F = 0.0129

. test x7 x9 x11

( 1) x7 = 0  
 ( 2) x9 = 0  
 ( 3) x11 = 0  
 F( 3, 3) = 24.62  
 Prob > F = 0.0129

. test x8 x10 x12

```

. predict u9,r
.
. predict y9hat,xb
.
. reg lnb x1 x2 x3 x4 x5 x6 x7 x8 x9 x10 x11 x12 x13 x14 l.u9,robust cluster(PD)

```

Linear regression

Number of obs =	2044
F( 2, 3) =	.
Prob > F =	.
R-squared =	0.0486
Root MSE =	.19143

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	.5234328	.2704946	1.94	0.148	-.3374018	1.384267
x2	-.0062145	.0020169	-3.08	0.054	-.0126331	.000204
x3	-.8789259	.5377194	-1.63	0.201	-2.590189	.8323373
x4	.0178614	.0164069	1.09	0.356	-.0343528	.0700756
x5	.3844166	.262365	1.47	0.239	-.450546	1.219379
x6	-.0521269	.0022345	-23.33	0.000	-.0592382	-.0450156
x7	-.7715081	.105616	-7.30	0.005	-1.107625	-.435391
x8	.0903525	.049028	1.84	0.163	-.0656766	.2463816
x9	.8096754	.1336406	6.06	0.009	.3843713	1.23498
x10	-.0907136	.0484896	-1.87	0.158	-.2450293	.0636021
x11	-.6399019	.14452	-4.43	0.021	-1.099829	-.1799747
x12	.1462445	.0067959	21.52	0.000	.1246169	.1678721
x13	-.0001521	.0001002	-1.52	0.226	-.0004709	.0001667
x14	-.0000312	.0000115	-2.70	0.073	-.0000679	5.51e-06
u9						
L1.	-.0174063	.0033928	-5.13	0.014	-.0282038	-.0066087
_cons	.0322585	.0050614	6.37	0.008	.0161509	.0483662

```

. gen y92=y9hat*y9hat
.
. gen y93=y92*y9hat
.
. reg lnb x1 x2 x3 x4 x5 x6 x7 x8 x9 x10 x11 x12 x13 x14 y92 y93, robust cluster(> PD)

```

Linear regression

Number of obs =	2048
F( 2, 3) =	.
Prob > F =	.
R-squared =	0.0541
Root MSE =	.19076

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	1.153999	.3239327	3.56	0.038	.1231006	2.184897
x2	-.0204888	.0052872	-3.88	0.030	-.037315	-.0036627
x3	-1.891874	.6023406	-3.14	0.052	-3.80879	.0250428
x4	.0448273	.0171718	2.61	0.080	-.0098209	.0994755
x5	.7996729	.2793286	2.86	0.064	-.0892755	1.688621
x6	-.1070674	.0110639	-9.68	0.002	-.1422777	-.071857
x7	-1.840855	.2720047	-6.77	0.007	-2.706495	-.9752148
x8	.2059353	.0499123	4.13	0.026	.0470922	.3647784
x9	1.917	.3212675	5.97	0.009	.8945832	2.939416
x10	-.2114609	.0516478	-4.09	0.026	-.3758274	-.0470944
x11	-1.396536	.2400403	-5.82	0.010	-2.160452	-.6326211
x12	.3006249	.0221531	13.57	0.001	.2301238	.371126
x13	-.0003273	.0001107	-2.96	0.060	-.0006797	.0000252
x14	-.0000624	.0000126	-4.95	0.016	-.0001026	-.0000223
y92	22.52321	4.801308	4.69	0.018	7.24331	37.80312
y93	92.6216	19.51165	4.75	0.018	30.5268	154.7164
_cons	.0607929	.0033742	18.02	0.000	.0500545	.0715312

```

. test y92 y93

```

- ( 1) y92 = 0
- ( 2) y93 = 0

F( 2, 3) = 11.27  
 Prob > F = 0.0403

. \*10 test all actual and season variables reservoir level

. reg lnb x1 x2 x3 x4 x5 x6,robust cluster(PD)

Linear regression

Number of obs = 2048  
 F( 2, 3) = .  
 Prob > F = 0.0387  
 R-squared = .19183  
 Root MSE = .19183

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	.0564619	.0052437	10.77	0.002	.0397742	.0731496
x2	.0008595	.0062033	0.14	0.899	-.018882	.0206011
x3	.0284305	.0138309	2.06	0.132	-.0155857	.0724467
x4	.0034251	.0202142	0.17	0.876	-.0609056	.0677558
x5	-.0884146	.0057855	-15.28	0.001	-.1068266	-.0700027
x6	-.0445562	.0021555	-20.67	0.000	-.051416	-.0376965
_cons	.0293277	.0054136	5.42	0.012	.0120992	.0465562

. test x1 x3 x5

- ( 1) x1 = 0
- ( 2) x3 = 0
- ( 3) x5 = 0

F( 3, 3) = 223.23  
 Prob > F = 0.0005

. test x2 x4 x6

- ( 1) x2 = 0
- ( 2) x4 = 0
- ( 3) x6 = 0

F( 3, 3) = 731.06  
 Prob > F = 0.0001

. predict u10,r

. predict y10hat,xb

. reg lnb x1 x2 x3 x4 x5 x6 l.u10,robust cluster(PD)

Linear regression

Number of obs = 2044  
 F( 2, 3) = .  
 Prob > F = 0.0390  
 R-squared = .19202  
 Root MSE = .19202

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	.0569685	.0054221	10.51	0.002	.039713	.0742239
x2	.0005119	.0063868	0.08	0.941	-.0198137	.0208375
x3	.0282071	.0140216	2.01	0.138	-.016416	.0728302
x4	.0036627	.0205567	0.18	0.870	-.0617578	.0690832
x5	-.0888029	.0057811	-15.36	0.001	-.1072008	-.070405
x6	-.0444514	.0022311	-19.92	0.000	-.0515519	-.0373509
u10						
l1.	-.0174317	.0055274	-3.15	0.051	-.0350223	.0001589
_cons	.0294021	.0054467	5.40	0.012	.0120683	.046736

```

. gen y102=y10hat*y10hat
.
. gen y103=y102*y10hat
.
. reg lnb x1 x2 x3 x4 x5 x6 y102 y103, robust cluster(PD)
Linear regression                               Number of obs =    2048
                                                F( 2, 3) = .
                                                Prob > F = .
                                                R-squared = 0.0391
                                                Root MSE = 0.19188

```

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	.0348677	.0219911	1.59	0.211	-.035118	.1048533
x2	-.0016078	.0055386	-0.29	0.791	-.019234	.0160184
x3	.0295458	.0164187	1.80	0.170	-.022706	.0817975
x4	.0046485	.0183032	0.25	0.816	-.0536005	.0628975
x5	-.0671037	.0171741	-3.91	0.030	-.1217595	-.0124479
x6	-.0373148	.0150455	-2.48	0.089	-.0851963	.0105668
y102	-.6176323	6.687414	-0.09	0.932	-21.89997	20.6647
y103	8.075343	32.40055	0.25	0.819	-95.03767	111.1884
_cons	.0247386	.0007373	33.55	0.000	.0223922	.0270851

```

. test y102 y103
( 1) y102 = 0
( 2) y103 = 0
      F( 2, 3) = 6.12
      Prob > F = 0.0874
.

```

. \*11 test all actual and season variables inflow

. reg lnb x7 x8 x9 x10 x11 x12,robust cluster(PD)

Linear regression Number of obs = **2048**  
 F( 2, 3) = .  
 Prob > F = .  
 R-squared = **0.0381**  
 Root MSE = **.19189**

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x7	<b>-.6547355</b>	<b>.1940202</b>	<b>-3.37</b>	<b>0.043</b>	<b>-1.272194</b>	<b>-.0372766</b>
x8	<b>-.001265</b>	<b>.0367217</b>	<b>-0.03</b>	<b>0.975</b>	<b>-.1181299</b>	<b>.1155999</b>
x9	<b>.3186986</b>	<b>.135473</b>	<b>2.35</b>	<b>0.100</b>	<b>-.1124368</b>	<b>.749834</b>
x10	<b>-.0429777</b>	<b>.0527887</b>	<b>-0.81</b>	<b>0.475</b>	<b>-.2109749</b>	<b>.1250194</b>
x11	<b>-.3177174</b>	<b>.0926298</b>	<b>-3.43</b>	<b>0.042</b>	<b>-.6125067</b>	<b>-.022928</b>
x12	<b>.0043415</b>	<b>.0095777</b>	<b>0.45</b>	<b>0.681</b>	<b>-.0261392</b>	<b>.0348222</b>
_cons	<b>.0164766</b>	<b>.011032</b>	<b>1.49</b>	<b>0.232</b>	<b>-.0186322</b>	<b>.0515855</b>

. test x7 x9 x11

- ( 1) **x7 = 0**
- ( 2) **x9 = 0**
- ( 3) **x11 = 0**

F( 3, 3) = **27.59**  
 Prob > F = **0.0110**

. test x8 x10 x12

- ( 1) **x8 = 0**
- ( 2) **x10 = 0**
- ( 3) **x12 = 0**

F( 3, 3) = **0.85**  
 Prob > F = **0.5516**

. predict u11,r

. predict y11hat,xb

. reg lnb x7 x8 x9 x10 x11 x12 l.u11,robust cluster(PD)

Linear regression Number of obs = **2044**  
 F( 2, 3) = .  
 Prob > F = .  
 R-squared = **0.0383**  
 Root MSE = **.19209**

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x7	<b>-.6597921</b>	<b>.1944904</b>	<b>-3.39</b>	<b>0.043</b>	<b>-1.278747</b>	<b>-.040837</b>
x8	<b>.0013648</b>	<b>.0372131</b>	<b>0.04</b>	<b>0.973</b>	<b>-.117064</b>	<b>.1197936</b>
x9	<b>.322523</b>	<b>.1353268</b>	<b>2.38</b>	<b>0.097</b>	<b>-.1081473</b>	<b>.7531934</b>
x10	<b>-.0433797</b>	<b>.0533503</b>	<b>-0.81</b>	<b>0.476</b>	<b>-.2131642</b>	<b>.1264047</b>
x11	<b>-.3207853</b>	<b>.0929239</b>	<b>-3.45</b>	<b>0.041</b>	<b>-.6165106</b>	<b>-.0250601</b>
x12	<b>.004511</b>	<b>.0100133</b>	<b>0.45</b>	<b>0.683</b>	<b>-.0273559</b>	<b>.0363779</b>
u11						
l1.	<b>-.0180837</b>	<b>.0050724</b>	<b>-3.57</b>	<b>0.038</b>	<b>-.0342262</b>	<b>-.0019412</b>
_cons	<b>.0165617</b>	<b>.0111711</b>	<b>1.48</b>	<b>0.235</b>	<b>-.0189896</b>	<b>.052113</b>

```

. gen y112=y11hat*y11hat
.
. gen y113=y112*y11hat
.
. reg lnb x7 x8 x9 x10 x11 x12 y112 y113, robust cluster(PD)
Linear regression                               Number of obs =    2048
                                                F( 2, 3) = .
                                                Prob > F = .
                                                R-squared = 0.0390
                                                Root MSE = 0.19189

```

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x7	-0.9864192	.2406557	-4.10	0.026	-1.752293	-.2205455
x8	-0.0037642	.0383019	-0.10	0.928	-.1256579	.1181295
x9	.3761556	.0695098	5.41	0.012	.1549444	.5973668
x10	-0.0606712	.0431394	-1.41	0.254	-.19796	.0766176
x11	-0.4760506	.1416244	-3.36	0.044	-.9267627	-.0253386
x12	.0103909	.0122518	0.85	0.459	-.0285999	.0493817
y112	13.47614	6.706944	2.01	0.138	-7.868353	34.82062
y113	56.62483	25.15019	2.25	0.110	-23.41429	136.6639
_cons	.0318185	.0162507	1.96	0.145	-.0198983	.0835354

```

. test y112 y113
( 1) y112 = 0
( 2) y113 = 0
      F( 2, 3) = 5.10
      Prob > F = 0.1083

```

. \*12 test all actual and season variables snow

. reg lnb x13 x14,robust cluster(PD)

Linear regression

Number of obs =	2048
F( 2, 3) =	13.79
Prob > F =	0.0307
R-squared =	0.0121
Root MSE =	.19428

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x13	.0000126	6.98e-06	1.80	0.170	-9.65e-06	.0000348
x14	-.0000363	6.95e-06	-5.23	0.014	-.0000584	-.0000142
_cons	-.0155608	.0180543	-0.86	0.452	-.0730177	.0418962

. predict u12,r

. predict y12hat,xb

. reg lnb x13 x14 l.u12,robust cluster(PD)

Linear regression

Number of obs =	2044
F( 2, 3) =	.
Prob > F =	.
R-squared =	0.0122
Root MSE =	.19448

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x13	.0000122	6.88e-06	1.78	0.173	-9.64e-06	.0000341
x14	-.0000362	6.95e-06	-5.21	0.014	-.0000583	-.0000141
u12	.0133849	.0187118	0.72	0.526	-.0461644	.0729343
_cons	-.0154958	.0176317	-0.88	0.444	-.0716079	.0406163

. gen y122=y12hat\*y12hat

. gen y123=y122\*y12hat

. reg lnb x13 x14 y122 y123, robust cluster(PD)

Linear regression

Number of obs =	2048
F( 2, 3) =	.
Prob > F =	.
R-squared =	0.0132
Root MSE =	.19426

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x13	-.0000315	.0000179	-1.76	0.177	-.0000884	.0000255
x14	.0000687	.0000514	1.34	0.273	-.0000948	.0002322
y122	-44.10404	37.85275	-1.17	0.328	-164.5684	76.36031
y123	-197.5093	233.837	-0.84	0.460	-941.6831	546.6646
_cons	-.0116076	.0243937	-0.48	0.667	-.0892391	.066024

. test y122 y123

( 1) y122 = 0

( 2) y123 = 0

F( 2, 3) =	19.65
Prob > F =	0.0189



. \*13 Test all diff. variables

. reg lnb x15 x16 x17 x18 x19 x20 x21,robust cluster(PD)

```

Linear regression                               Number of obs =    2048
                                                F( 2, 2045) =      .
                                                Prob > F          =      .
                                                R-squared        =    0.0050
                                                Root MSE        =    .19521

```

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x15	.0289518	.0168836	1.71	0.185	-.0247793	.0826829
x16	-.0226157	.0116956	-1.93	0.149	-.0598364	.014605
x17	-.0415273	.0077725	-5.34	0.013	-.0662629	-.0167917
x18	-.0547407	.0805402	-0.68	0.545	-.3110555	.201574
x19	.131239	.0815818	1.61	0.206	-.1283907	.3908688
x20	.0762529	.0258485	2.95	0.060	-.0060087	.1585145
x21	-.0000319	.0000125	-2.55	0.084	-.0000718	7.90e-06
_cons	-.0341722	.0184599	-1.85	0.161	-.0929198	.0245755

. test x15 x16 x17

- ( 1) x15 = 0
- ( 2) x16 = 0
- ( 3) x17 = 0

F( 3, 2042) = 433.16  
 Prob > F = 0.0002

. test x18 x19 x20

- ( 1) x18 = 0
- ( 2) x19 = 0
- ( 3) x20 = 0

F( 3, 2042) = 47.47  
 Prob > F = 0.0050

. predict u13,r

. predict y13hat,xb

. reg lnb x15 x16 x17 x18 x19 x20 x21 l.u13,robust cluster(PD)

```

Linear regression                               Number of obs =    2044
                                                F( 2, 2041) =      .
                                                Prob > F          =      .
                                                R-squared        =    0.0053
                                                Root MSE        =    .19541

```

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x15	.0275046	.0180988	1.52	0.226	-.0300939	.085103
x16	-.0214709	.0114773	-1.87	0.158	-.0579967	.0150549
x17	-.0413998	.0077048	-5.37	0.013	-.06592	-.0168795
x18	-.0527115	.0815746	-0.65	0.564	-.3123183	.2068953
x19	.1257684	.0863529	1.46	0.241	-.1490449	.4005817
x20	.0778747	.0275701	2.82	0.066	-.0098657	.1656151
x21	-.0000319	.0000126	-2.53	0.086	-.0000721	8.27e-06
u13						
l1.	.018717	.0197992	0.95	0.414	-.0442931	.081727
_cons	-.0342888	.0182364	-1.88	0.157	-.0923251	.0237475

```

. gen y132=y13hat*y13hat
.
. gen y133=y132*y13hat
.
. reg lnb x15 x16 x17 x18 x19 x20 x21 y132 y133, robust cluster(PD)
Linear regression                               Number of obs =   2048
                                                F( 2, 3) = .
                                                Prob > F = .
                                                R-squared = 0.0120
                                                Root MSE = 0.19462

```

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x15	-.0215551	.0203189	-1.06	0.367	-.086219	.0431087
x16	.0133104	.0294562	0.45	0.682	-.0804322	.1070531
x17	.0091748	.0492294	0.19	0.864	-.1474952	.1658449
x18	.0688251	.0108029	6.37	0.008	.0344455	.1032047
x19	-.0417038	.0625726	-0.67	0.553	-.2408376	.15743
x20	-.0517109	.0998215	-0.52	0.640	-.3693876	.2659657
x21	.0000237	.000026	0.91	0.430	-.0000592	.0001066
y132	17.62156	17.72868	0.99	0.394	-38.79901	74.04214
y133	552.7242	91.68972	6.03	0.009	260.9266	844.5218
_cons	-.0253459	.0364305	-0.70	0.537	-.1412841	.0905922

```

. test y132 y133
( 1) y132 = 0
( 2) y133 = 0
      F( 2, 3) = 22.69
      Prob > F = 0.0154

```

```
. *14 Test diff. variables reservoir level
```

```
. reg lnb x15 x16 x17,robust cluster(PD)
```

```
Linear regression
```

```
Number of obs = 2048
F( 2, 3) = .
Prob > F = .
R-squared = 0.0021
Root MSE = .1953
```

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x15	.0095764	.0085625	1.12	0.345	-.0176733	.0368262
x16	-.0156439	.0126318	-1.24	0.304	-.0558441	.0245562
x17	-.0318554	.0068507	-4.65	0.019	-.0536574	-.0100534
_cons	-.0349629	.0180621	-1.94	0.148	-.0924444	.0225187

```
. predict u14,r
```

```
. predict y14hat,xb
```

```
. reg lnb x15 x16 x17 l.u14,robust cluster(PD)
```

```
Linear regression
```

```
Number of obs = 2044
F( 2, 3) = .
Prob > F = .
R-squared = 0.0026
Root MSE = .19548
```

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x15	.0083538	.0091306	0.91	0.428	-.0207037	.0374114
x16	-.0152294	.0121868	-1.25	0.300	-.0540131	.0235543
x17	-.0314848	.0066617	-4.73	0.018	-.0526853	-.0102843
u14						
l1.	.0214851	.0213741	1.01	0.389	-.0465368	.0895069
_cons	-.0350688	.017738	-1.98	0.142	-.0915189	.0213813

```
. gen y142=y14hat*y14hat
```

```
. gen y143=y142*y14hat
```

```
. reg lnb x15 x16 x17 y142 y143, robust cluster(PD)
```

```
Linear regression
```

```
Number of obs = 2048
F( 2, 3) = .
Prob > F = .
R-squared = 0.0057
Root MSE = .19504
```

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x15	.0447667	.0283685	1.58	0.213	-.0455144	.1350478
x16	-.1025676	.0453705	-2.26	0.109	-.2469568	.0418217
x17	-.1972492	.0978529	-2.02	0.137	-.5086606	.1141623
y142	282.601	153.3445	1.84	0.163	-205.4095	770.6116
y143	3708.264	1981.304	1.87	0.158	-2597.128	10013.66
_cons	-.2150404	.0885288	-2.43	0.093	-.4967786	.0666977

```
. test y142 y143
```

```
( 1) y142 = 0
( 2) y143 = 0
```

```
F( 2, 3) = 1.78
Prob > F = 0.3099
```

. \*15 Test diff. variables inflow

. reg ln b x18 x19 x20,robust cluster(PD)

Linear regression Number of obs = 2048  
F( 2, 3) = .  
Prob > F = .  
R-squared = 0.0004  
Root MSE = .19547

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x18	-.1112366	.0513997	-2.16	0.119	-.2748135	.0523402
x19	.0947652	.0716479	1.32	0.278	-.1332504	.3227809
x20	-.0186232	.0040628	-4.58	0.019	-.0315526	-.0056937
_cons	-.0336885	.017552	-1.92	0.151	-.0895468	.0221698

. predict u15,r

. predict y15hat,xb

. reg ln b x18 x19 x20 l.u15,robust cluster(PD)

Linear regression Number of obs = 2044  
F( 2, 3) = .  
Prob > F = .  
R-squared = 0.0007  
Root MSE = .19566

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x18	-.1107225	.0508907	-2.18	0.118	-.2726794	.0512345
x19	.0904586	.0743675	1.22	0.311	-.1462119	.3271291
x20	-.017614	.0036772	-4.79	0.017	-.0293165	-.0059116
u15						
L1.	.0193897	.0198652	0.98	0.401	-.0438302	.0826096
_cons	-.0337783	.0172515	-1.96	0.145	-.0886802	.0211237

. gen y152=y15hat\*y15hat

. gen y153=y152\*y15hat

. reg ln b x15 x16 x17 y152 y153, robust cluster(PD)

Linear regression Number of obs = 2048  
F( 3, 3) = .  
Prob > F = .  
R-squared = 0.0097  
Root MSE = .19465

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x15	.021799	.0155956	1.40	0.257	-.0278333	.0714313
x16	-.0089002	.0087844	-1.01	0.386	-.0368559	.0190555
x17	-.0403221	.0037295	-10.81	0.002	-.052191	-.0284532
y152	396.4308	75.89171	5.22	0.014	154.9095	637.9521
y153	8038.733	1757.8	4.57	0.020	2444.63	13632.84
_cons	-.1717727	.0077234	-22.24	0.000	-.1963522	-.1471933

. test y152 y153

( 1) y152 = 0  
( 2) y153 = 0

F( 2, 3) = 45.62  
Prob > F = 0.0057

. \*16 Test diff. variables snow

. reg lnb x21,robust cluster(PD)

Linear regression

Number of obs = 2048  
 F( 1, 3) = 27.42  
 Prob > F = 0.0136  
 R-squared = 0.0027  
 Root MSE = .19514

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x21	-.0000364	6.95e-06	-5.24	0.014	-.0000585	-.0000143
_cons	-.0339863	.017389	-1.95	0.146	-.0893257	.0213531

. predict u16,r

. predict y16hat,xb

. reg lnb x21 l.u16,robust cluster(PD)

Linear regression

Number of obs = 2044  
 F( 2, 3) = 21.75  
 Prob > F = 0.0164  
 R-squared = 0.0031  
 Root MSE = .19533

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x21	-.0000364	7.02e-06	-5.18	0.014	-.0000587	-.000014
u16	.0208942	.0204316	1.02	0.382	-.0441282	.0859166
_cons	-.0340486	.0170438	-2.00	0.140	-.0882894	.0201923

. gen y162=y16hat\*y16hat

. gen y163=y162\*y16hat

. reg lnb x21 y162 y163, robust cluster(PD)

Linear regression

Number of obs = 2048  
 F( 2, 3) = .  
 Prob > F = .  
 R-squared = 0.0143  
 Root MSE = .1941

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x21	.0004327	.0001462	2.96	0.060	-.0000326	.0008979
y162	-266.9874	92.02519	-2.90	0.062	-559.8526	25.87786
y163	-1504.239	598.0592	-2.52	0.087	-3407.53	399.0526
_cons	.2258855	.0981958	2.30	0.105	-.0866173	.5383884

. test y162 y163

( 1) y162 = 0  
 ( 2) y163 = 0

F( 2, 3) = 13.29  
 Prob > F = 0.0323

. \*17 test all actual variables and diff. variables

. reg lnb x2 x4 x6 x8 x10 x12 x14 x15 x16 x17 x18 x19 x20 x21,robust cluster(PD)

Linear regression

Number of obs =	2048
F( 2, 3) =	.
Prob > F =	.
R-squared =	0.0484
Root MSE =	.19123

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	.5179542	.2609828	1.98	0.141	-.3126094	1.348518
x4	-.8632192	.5042434	-1.71	0.185	-2.467947	.7415083
x6	.3338772	.2553351	1.31	0.282	-.478713	1.146467
x8	-.6807216	.1235944	-5.51	0.012	-1.074054	-.2873892
x10	.7165293	.1722098	4.16	0.025	.1684808	1.264578
x12	-.4922659	.1398638	-3.52	0.039	-.937375	-.0471569
x14	-.0001838	.0001067	-1.72	0.183	-.0005234	.0001558
x15	-.5243376	.2607051	-2.01	0.138	-1.354018	.3053424
x16	.8810809	.5197107	1.70	0.189	-.7728704	2.535032
x17	-.385821	.2538872	-1.52	0.226	-1.193803	.4221612
x18	.769805	.1032477	7.46	0.005	.4412247	1.098385
x19	-.8071929	.1259147	-6.41	0.008	-1.20791	-.406476
x20	.6385797	.137491	4.64	0.019	.2010219	1.076137
x21	.0001524	.0000967	1.58	0.213	-.0001552	.0004601
_cons	.032259	.0049749	6.48	0.007	.0164267	.0480912

. test x2 x4 x6 x15 x16 x17

( 1) x2 = 0  
( 2) x4 = 0  
( 3) x6 = 0  
( 4) x15 = 0  
( 5) x16 = 0  
( 6) x17 = 0  
Constraint 3 dropped  
Constraint 4 dropped  
Constraint 6 dropped  
F( 3, 3) = 62.90  
Prob > F = 0.0033

. test x2 x4 x6

( 1) x2 = 0  
( 2) x4 = 0  
( 3) x6 = 0  
F( 3, 3) = 320.21  
Prob > F = 0.0003

. test x15 x16 x17

( 1) x15 = 0  
( 2) x16 = 0  
( 3) x17 = 0  
F( 3, 3) = 235.93  
Prob > F = 0.0005

. test x8 x10 x12 x18 x19 x20

( 1) x8 = 0  
( 2) x10 = 0  
( 3) x12 = 0  
( 4) x18 = 0  
( 5) x19 = 0  
( 6) x20 = 0  
Constraint 1 dropped  
Constraint 3 dropped  
Constraint 5 dropped  
F( 3, 3) = 111.04  
Prob > F = 0.0014

. test x8 x10 x12

( 1) x8 = 0  
( 2) x10 = 0  
( 3) x12 = 0  
F( 3, 3) = 65.06  
Prob > F = 0.0031

. test x18 x19 x20

```

. predict u17,r
.
. predict y17hat,xb
.
. reg lnb x2 x4 x6 x8 x10 x12 x14 x15 x16 x17 x18 x19 x20 x21 l.u17,robust cluste
> r(PD)

```

Linear regression

Number of obs =	2044
F( 2, 3) =	.
Prob > F =	.
R-squared =	0.0486
Root MSE =	.19144

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	.51343	.2674217	1.92	0.151	-.3376252	1.364485
x4	-.8551041	.5164193	-1.66	0.196	-2.498581	.7883724
x6	.330137	.2613404	1.26	0.296	-.5015649	1.161839
x8	-.6783557	.1256966	-5.40	0.012	-1.078378	-.2783329
x10	.7126597	.1757195	4.06	0.027	.1534417	1.271878
x12	-.4902687	.1435502	-3.42	0.042	-.9471095	-.0334278
x14	-.0001821	.0001092	-1.67	0.194	-.0005296	.0001653
x15	-.5196093	.2669469	-1.95	0.147	-1.369153	.3299349
x16	.8729543	.5320537	1.64	0.199	-.8202779	2.566186
x17	-.382289	.2602285	-1.47	0.238	-1.210452	.4458744
x18	.7686212	.1044496	7.36	0.005	.4362158	1.101026
x19	-.8033388	.1282122	-6.27	0.008	-1.211367	-.3953104
x20	.6365383	.1415205	4.50	0.021	.1861569	1.08692
x21	.000151	.0000991	1.52	0.225	-.0001643	.0004662
u17						
l1.	-.0174272	.0033991	-5.13	0.014	-.0282447	-.0066098
_cons	.0322635	.0050585	6.38	0.008	.0161653	.0483618

```

. gen y172=y17hat*y17hat
.
. gen y173=y172*y17hat
.
. reg lnb x2 x4 x6 x8 x10 x12 x14 x15 x16 x17 x18 x19 x20 x21 y172 y173, robust c
> luster(PD)

```

Linear regression

Number of obs =	2048
F( 2, 3) =	.
Prob > F =	.
R-squared =	0.0540
Root MSE =	.19076

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	1.123904	.3154672	3.56	0.038	.1199466	2.127862
x4	-1.83206	.5747503	-3.19	0.050	-3.661172	-.0029476
x6	.6873318	.2711493	2.53	0.085	-.1755864	1.55025
x8	-1.625936	.2645433	-6.15	0.009	-2.467831	-.7840409
x10	1.689012	.308337	5.48	0.012	.7077464	2.670279
x12	-1.086782	.2119849	-5.13	0.014	-1.761413	-.4121516
x14	-.0003868	.0001202	-3.22	0.049	-.0007694	-4.27e-06
x15	-1.144241	.3167023	-3.61	0.036	-2.152129	-.136353
x16	1.876765	.5909854	3.18	0.050	-.0040142	3.757544
x17	-.7942792	.2750065	-2.89	0.063	-1.669473	.0809143
x18	1.830958	.2652134	6.90	0.006	.9869302	2.674985
x19	-1.899799	.3099033	-6.13	0.009	-2.88605	-.9135482
x20	1.386821	.2325021	5.96	0.009	.6468951	2.126746
x21	.0003245	.0001087	2.99	0.058	-.0000213	.0006704
y172	22.44394	4.707875	4.77	0.018	7.461386	37.4265
y173	92.30654	19.1588	4.82	0.017	31.3347	153.2784
_cons	.0607047	.0033044	18.37	0.000	.0501886	.0712208

```

. test y172 y173
( 1) y172 = 0
( 2) y173 = 0
F( 2, 3) = 11.61
Prob > F = 0.0387

```

. \*18 test all actual variables and diff. variables reservoir level

. reg lnb x2 x4 x6 x15 x16 x17,robust cluster(PD)

Linear regression

Number of obs = 2048  
 F( 2, 3) = .  
 Prob > F = .  
 R-squared = 0.0387  
 Root MSE = .19183

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	.0572902	.0097383	5.88	0.010	.0262987	.0882817
x4	.0318737	.0102565	3.11	0.053	-.0007671	.0645144
x6	-.132956	.0041681	-31.90	0.000	-.1462207	-.1196913
x15	-.0563907	.0052397	-10.76	0.002	-.0730656	-.0397157
x16	-.0284648	.0138057	-2.06	0.131	-.0724007	.015471
x17	.0883814	.0057894	15.27	0.001	.0699569	.1068059
_cons	.0293308	.0054144	5.42	0.012	.0120999	.0465617

. test x2 x4 x6

- ( 1) x2 = 0
- ( 2) x4 = 0
- ( 3) x6 = 0

F( 3, 3) = 2792.09  
 Prob > F = 0.0000

. test x15 x16 x17

- ( 1) x15 = 0
- ( 2) x16 = 0
- ( 3) x17 = 0

F( 3, 3) = 223.88  
 Prob > F = 0.0005

. predict u18,r

. predict y18hat,xb

. reg lnb x2 x4 x6 x15 x16 x17 l.u18,robust cluster(PD)

Linear regression

Number of obs = 2044  
 F( 2, 3) = .  
 Prob > F = .  
 R-squared = 0.0390  
 Root MSE = .19202

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	.0574496	.0097855	5.87	0.010	.0263077	.0885914
x4	.0318875	.010331	3.09	0.054	-.0009904	.0647654
x6	-.1332395	.0042114	-31.64	0.000	-.146642	-.1198371
x15	-.0568977	.005417	-10.50	0.002	-.0741371	-.0396583
x16	-.0282413	.0139951	-2.02	0.137	-.07278	.0162974
x17	.0887699	.0057851	15.34	0.001	.0703592	.1071807
u18						
l1.	-.0174321	.0055273	-3.15	0.051	-.0350226	.0001583
_cons	.0294052	.0054476	5.40	0.012	.0120686	.0467417



```

. gen y182=y18hat*y18hat
.
. gen y183=y182*y18hat
.
. reg lnb x2 x4 x6 x15 x16 x17 y182 y183, robust cluster(PD)
Linear regression                               Number of obs =    2048
                                                F( 2,          3) =    .
                                                Prob > F        =    .
                                                R-squared       =    0.0391
                                                Root MSE       =    .19188

```

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	.0332553	.0264195	1.26	0.297	-.0508233	.1173338
x4	.0342097	.0043753	7.82	0.004	.0202856	.0481338
x6	-.104437	.0321196	-3.25	0.047	-.206656	-.0022181
x15	-.0348324	.0220091	-1.58	0.212	-.1048753	.0352104
x16	-.0295718	.0164021	-1.80	0.169	-.0817706	.022627
x17	.0670991	.0171692	3.91	0.030	.0124589	.1217393
y182	-.6135028	6.688817	-0.09	0.933	-21.9003	20.6733
y183	8.094114	32.40672	0.25	0.819	-95.03852	111.2267
_cons	.0247467	.0007376	33.55	0.000	.0223993	.0270941

```

. test y182 y183
( 1) y182 = 0
( 2) y183 = 0
      F( 2,          3) =    6.11
      Prob > F        =    0.0875

```

. \*19 test all actual variables and diff. variables inflow

. reg lnb x8 x10 x12 x18 x19 x20,robust cluster(PD)

Linear regression Number of obs = **2048**  
 F( 2, 3) = .  
 Prob > F = .  
 R-squared = **0.0381**  
 Root MSE = **.19189**

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x8	<b>-.6560004</b>	<b>.219655</b>	<b>-2.99</b>	<b>0.058</b>	<b>-1.355041</b>	<b>.0430397</b>
x10	<b>.2757207</b>	<b>.1837357</b>	<b>1.50</b>	<b>0.230</b>	<b>-.3090082</b>	<b>.8604496</b>
x12	<b>-.3133758</b>	<b>.0888241</b>	<b>-3.53</b>	<b>0.039</b>	<b>-.5960537</b>	<b>-.0306979</b>
x18	<b>.6547354</b>	<b>.1940203</b>	<b>3.37</b>	<b>0.043</b>	<b>.0372763</b>	<b>1.272195</b>
x19	<b>-.3186984</b>	<b>.135473</b>	<b>-2.35</b>	<b>0.100</b>	<b>-.749834</b>	<b>.1124372</b>
x20	<b>.3177173</b>	<b>.0926298</b>	<b>3.43</b>	<b>0.042</b>	<b>.0229279</b>	<b>.6125067</b>
_cons	<b>.0164766</b>	<b>.011032</b>	<b>1.49</b>	<b>0.232</b>	<b>-.0186322</b>	<b>.0515855</b>

. test x8 x10 x12

- ( 1) **x8 = 0**
- ( 2) **x10 = 0**
- ( 3) **x12 = 0**

F( 3, 3) = **1007.85**  
 Prob > F = **0.0001**

. test x18 x19 x20

- ( 1) **x18 = 0**
- ( 2) **x19 = 0**
- ( 3) **x20 = 0**

F( 3, 3) = **27.59**  
 Prob > F = **0.0110**

. predict u19,r

. predict y19hat,xb

. reg lnb x8 x10 x12 x18 x19 x20 l.u19,robust cluster(PD)

Linear regression Number of obs = **2044**  
 F( 2, 3) = .  
 Prob > F = .  
 R-squared = **0.0383**  
 Root MSE = **.19209**

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x8	<b>-.6584271</b>	<b>.2206404</b>	<b>-2.98</b>	<b>0.058</b>	<b>-1.360603</b>	<b>.043749</b>
x10	<b>.2791432</b>	<b>.183912</b>	<b>1.52</b>	<b>0.226</b>	<b>-.306147</b>	<b>.8644334</b>
x12	<b>-.3162743</b>	<b>.0890491</b>	<b>-3.55</b>	<b>0.038</b>	<b>-.5996684</b>	<b>-.0328802</b>
x18	<b>.6597919</b>	<b>.1944904</b>	<b>3.39</b>	<b>0.043</b>	<b>.0408366</b>	<b>1.278747</b>
x19	<b>-.3225229</b>	<b>.1353269</b>	<b>-2.38</b>	<b>0.097</b>	<b>-.7531934</b>	<b>.1081476</b>
x20	<b>.3207853</b>	<b>.0929239</b>	<b>3.45</b>	<b>0.041</b>	<b>.02506</b>	<b>.6165106</b>
u19						
l1.	<b>-.0180837</b>	<b>.0050724</b>	<b>-3.57</b>	<b>0.038</b>	<b>-.0342262</b>	<b>-.0019412</b>
_cons	<b>.0165617</b>	<b>.0111711</b>	<b>1.48</b>	<b>0.235</b>	<b>-.0189896</b>	<b>.052113</b>

```
. gen y192=y19hat*y19hat
```

```
. gen y193=y192*y19hat
```

```
. reg lnb x8 x10 x12 x18 x19 x20 y192 y193, robust cluster(PD)
```

Linear regression

Number of obs = **2048**  
F( 2, 3) = .  
Prob > F = **0.0390**  
R-squared = **0.0390**  
Root MSE = **.19189**

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x8	<b>-.9901831</b>	<b>.2744014</b>	<b>-3.61</b>	<b>0.037</b>	<b>-1.863451</b>	<b>-.1169153</b>
x10	<b>.3154842</b>	<b>.0954812</b>	<b>3.30</b>	<b>0.046</b>	<b>.0116204</b>	<b>.6193479</b>
x12	<b>-.4656596</b>	<b>.1327427</b>	<b>-3.51</b>	<b>0.039</b>	<b>-.8881061</b>	<b>-.0432131</b>
x18	<b>.9864189</b>	<b>.2406557</b>	<b>4.10</b>	<b>0.026</b>	<b>.2205451</b>	<b>1.752293</b>
x19	<b>-.3761554</b>	<b>.0695098</b>	<b>-5.41</b>	<b>0.012</b>	<b>-.5973665</b>	<b>-.1549442</b>
x20	<b>.4760505</b>	<b>.1416244</b>	<b>3.36</b>	<b>0.044</b>	<b>.0253383</b>	<b>.9267627</b>
y192	<b>13.47613</b>	<b>6.706946</b>	<b>2.01</b>	<b>0.138</b>	<b>-7.868363</b>	<b>34.82063</b>
y193	<b>56.62481</b>	<b>25.1502</b>	<b>2.25</b>	<b>0.110</b>	<b>-23.41434</b>	<b>136.664</b>
_cons	<b>.0318185</b>	<b>.0162507</b>	<b>1.96</b>	<b>0.145</b>	<b>-.0198983</b>	<b>.0835354</b>

```
. test y192 y193
```

```
( 1) y192 = 0
```

```
( 2) y193 = 0
```

F( 2, 3) = **5.10**  
Prob > F = **0.1083**

```
. *20 test all actual variables and diff. variables snow
```

```
. reg lnb x14 x21,robust cluster(PD)
```

```
Linear regression
```

Number of obs =	2048
F( 2, 3) =	13.79
Prob > F =	0.0307
R-squared =	0.0121
Root MSE =	.19428

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x14	-.0000238	7.41e-06	-3.20	0.049	-.0000473	-1.61e-07
x21	-.0000126	6.98e-06	-1.80	0.170	-.0000348	9.65e-06
_cons	-.0155608	.0180543	-0.86	0.452	-.0730177	.0418962

```
. predict u20,r
```

```
. predict y20hat,xb
```

```
. reg lnb x14 x21 l.u20,robust cluster(PD)
```

```
Linear regression
```

Number of obs =	2044
F( 2, 3) =	.
Prob > F =	.
R-squared =	0.0122
Root MSE =	.19448

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x14	-.0000239	7.10e-06	-3.37	0.043	-.0000465	-1.34e-06
x21	-.0000122	6.88e-06	-1.78	0.173	-.0000341	9.64e-06
u20						
l1.	.0133849	.0187118	0.72	0.526	-.0461644	.0729343
_cons	-.0154958	.0176317	-0.88	0.444	-.0716079	.0406163

```
. gen y202=y20hat*y20hat
```

```
. gen y203=y202*y20hat
```

```
. reg lnb x14 x21 y202 y203, robust cluster(PD)
```

```
Linear regression
```

Number of obs =	2048
F( 2, 3) =	.
Prob > F =	.
R-squared =	0.0132
Root MSE =	.19426

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x14	.0000372	.0000345	1.08	0.359	-.0000725	.000147
x21	.0000315	.0000179	1.76	0.177	-.0000255	.0000884
y202	-44.10402	37.85276	-1.17	0.328	-164.5684	76.36035
y203	-197.5091	233.8371	-0.84	0.460	-941.6831	546.6648
_cons	-.0116076	.0243937	-0.48	0.667	-.0892391	.066024

```
. test y202 y203
```

```
( 1) y202 = 0
( 2) y203 = 0
```

```
F( 2, 3) = 19.65
Prob > F = 0.0189
```

## Week

```
. xtfisher lnb, lags(5)
```

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

```
chi2(8) = 307.3450
Prob > chi2 = 0.0000
```

```
. xtfisher x1, lags(5)
```

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

```
chi2(8) = 472.6361
Prob > chi2 = 0.0000
```

```
. xtfisher x2, lags(5)
```

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

```
chi2(8) = 326.3535
Prob > chi2 = 0.0000
```

```
. xtfisher x3, lags(5)
```

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

```
chi2(8) = 449.0930
Prob > chi2 = 0.0000
```

```
. xtfisher x4, lags(5)
```

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

```
chi2(8) = 309.9961
Prob > chi2 = 0.0000
```

```
. xtfisher x5, lags(5)
```

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

```
chi2(8) = 372.9146
Prob > chi2 = 0.0000
```

```
. xtfisher x6, lags(5)
```

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

```
chi2(8) = 267.5229
Prob > chi2 = 0.0000
```

```
. xtfisher x7, lags(5)
```

```
Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)
```

```
Ho: unit root
```

```
chi2(8) = 397.6871  
Prob > chi2 = 0.0000
```

```
. xtfisher x8, lags(5)
```

```
Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)
```

```
Ho: unit root
```

```
chi2(8) = 280.1500  
Prob > chi2 = 0.0000
```

```
. xtfisher x9, lags(5)
```

```
Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)
```

```
Ho: unit root
```

```
chi2(8) = 370.1892  
Prob > chi2 = 0.0000
```

```
. xtfisher x10, lags(5)
```

```
Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)
```

```
Ho: unit root
```

```
chi2(8) = 258.2565  
Prob > chi2 = 0.0000
```

```
. xtfisher x11, lags(5)
```

```
Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)
```

```
Ho: unit root
```

```
chi2(8) = 370.8051  
Prob > chi2 = 0.0000
```

```
. xtfisher x12, lags(5)
```

```
Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)
```

```
Ho: unit root
```

```
chi2(8) = 227.2273  
Prob > chi2 = 0.0000
```

```
. xtfisher x13, lags(5)
```

```
Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)
```

```
Ho: unit root
```

```
chi2(8) = 493.9675  
Prob > chi2 = 0.0000
```

```
.
```

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(8) = 310.1591  
Prob > chi2 = 0.0000

. xtfisher x15, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(8) = 390.6567  
Prob > chi2 = 0.0000

. xtfisher x16, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(8) = 385.4685  
Prob > chi2 = 0.0000

. xtfisher x17, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(8) = 361.4644  
Prob > chi2 = 0.0000

. xtfisher x18, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(8) = 298.8879  
Prob > chi2 = 0.0000

. xtfisher x19, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(8) = 300.7455  
Prob > chi2 = 0.0000

. xtfisher x20, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(8) = 324.4936  
Prob > chi2 = 0.0000

. xtfisher x21, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(8) = 387.6408  
Prob > chi2 = 0.0000

. \*1 test actual variables

. reg lnb x2 x4 x6 x8 x10 x12 x14,robust cluster(PD)

Linear regression Number of obs = 2048  
F( 2, 3) = .  
Prob > F = .  
R-squared = 0.2407  
Root MSE = .3705

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	.1418731	.0268532	5.28	0.013	.0564141	.227332
x4	-.1244292	.0237943	-5.23	0.014	-.2001533	-.0487051
x6	-.0334968	.0091114	-3.68	0.035	-.0624934	-.0045002
x8	.3423878	.0731138	4.68	0.018	.1097071	.5750684
x10	.2993209	.0522736	5.73	0.011	.1329632	.4656787
x12	-.2089296	.0359577	-5.81	0.010	-.3233632	-.094496
x14	5.46e-06	2.49e-06	2.19	0.116	-2.47e-06	.0000134
_cons	-.408941	.0692251	-5.91	0.010	-.6292462	-.1886358

. test x2 x4 x6

- ( 1) x2 = 0
- ( 2) x4 = 0
- ( 3) x6 = 0

F( 3, 3) = 29.13  
Prob > F = 0.0102

. test x8 x10 x12

- ( 1) x8 = 0
- ( 2) x10 = 0
- ( 3) x12 = 0

F( 3, 3) = 14.75  
Prob > F = 0.0266

. predict u,r

. predict yhat,xb

. reg lnb x2 x4 x6 x8 x10 x12 x14 l.u,robust cluster(PD)

Linear regression Number of obs = 2044  
F( 2, 3) = .  
Prob > F = .  
R-squared = 0.2621  
Root MSE = .36566

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	.141981	.0265095	5.36	0.013	.0576161	.2263459
x4	-.1243115	.0233358	-5.33	0.013	-.1985764	-.0500466
x6	-.0353745	.0096259	-3.67	0.035	-.0660086	-.0047405
x8	.3641295	.0800983	4.55	0.020	.109221	.6190381
x10	.2765458	.0399676	6.92	0.006	.1493512	.4037405
x12	-.1873337	.0240433	-7.79	0.004	-.2638501	-.1108174
x14	1.78e-06	3.08e-06	0.58	0.605	-8.03e-06	.0000116
u						
l1.	-.1750743	.050906	-3.44	0.041	-.3370799	-.0130687
_cons	-.3874263	.0731569	-5.30	0.013	-.6202442	-.1546084



```

. gen y2=yhat*yhat
.
. gen y3=y2*yhat
.
. reg lnb x2 x4 x6 x8 x10 x12 x14 y2 y3, robust cluster(PD)
Linear regression                               Number of obs =    2048
                                                F( 2,          3) =    .
                                                Prob > F       =    .
                                                R-squared     =    0.2958
                                                Root MSE     =    .35697

                                                (Std. Err. adjusted for 4 clusters in PD)

```

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	.0410371	.035632	1.15	0.333	-.0723599	.1544341
x4	-.0390901	.0297548	-1.31	0.280	-.133783	.0556028
x6	-.0057052	.0078306	-0.73	0.519	-.0306256	.0192152
x8	.1639239	.0549258	2.98	0.058	-.0108745	.3387223
x10	.140783	.0696536	2.02	0.136	-.0808859	.362452
x12	-.0993294	.044555	-2.23	0.112	-.2411232	.0424643
x14	2.36e-06	2.77e-06	0.85	0.458	-6.47e-06	.0000112
y2	-1.321397	.4281179	-3.09	0.054	-2.683859	.0410653
y3	1.019059	.7847924	1.30	0.285	-1.478501	3.516619
_cons	-.1500632	.1579998	-0.95	0.412	-.6528892	.3527628

```

. test y2 y3
( 1) y2 = 0
( 2) y3 = 0
      F( 2,          3) =    97.16
      Prob > F =    0.0019

```

. \*2 test actual variables reservoir level

. reg lnb x2 x4 x6,robust cluster(PD)

Linear regression Number of obs = 2048  
F( 2, 3) = .  
Prob > F = .  
R-squared = 0.0712  
Root MSE = .40937

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	.0634692	.0113375	5.60	0.011	.0273881	.0995503
x4	-.0742137	.0130841	-5.67	0.011	-.1158531	-.0325744
x6	.0236948	.0061399	3.86	0.031	.0041548	.0432348
_cons	-.4341076	.0781938	-5.55	0.012	-.682955	-.1852601

. predict u2,r

. predict y2hat,xb

. reg lnb x2 x4 x6 l.u2,robust cluster(PD)

Linear regression Number of obs = 2044  
F( 2, 3) = .  
Prob > F = .  
R-squared = 0.1148  
Root MSE = .40011

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	.0589893	.0111928	5.27	0.013	.0233689	.0946096
x4	-.0695842	.0125005	-5.57	0.011	-.1093664	-.0298021
x6	.0206332	.0062454	3.30	0.046	.0007576	.0405088
u2						
L1.	-.2203911	.0281325	-7.83	0.004	-.3099214	-.1308608
_cons	-.4071052	.0827195	-4.92	0.016	-.6703555	-.143855

. gen y22=y2hat\*y2hat

. gen y23=y22\*y2hat

. reg lnb x2 x4 x6 y22 y23, robust cluster(PD)

Linear regression Number of obs = 2048  
F( 2, 3) = .  
Prob > F = .  
R-squared = 0.0731  
Root MSE = .40916

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	.0394478	.0304744	1.29	0.286	-.0575355	.1364311
x4	-.0477893	.0347707	-1.37	0.263	-.1584453	.0628667
x6	.017187	.0102654	1.67	0.193	-.0154819	.049856
y22	-3.540372	4.458962	-0.79	0.485	-17.73078	10.65003
y23	-6.60613	10.09311	-0.65	0.559	-38.72692	25.51466
_cons	-.265056	.2238517	-1.18	0.322	-.977452	.4473399

. test y22 y23

( 1) y22 = 0

( 2) y23 = 0

F( 2, 3) = 0.36  
Prob > F = 0.7270

. \*3 test actual variables inflow

. reg lnb x8 x10 x12,robust cluster(PD)

Linear regression

Number of obs =	2048
F( 2, 3) =	.
Prob > F =	.
R-squared =	0.1313
Root MSE =	.39591

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x8	.351227	.0590005	5.95	0.009	.1634611	.5389929
x10	.0480101	.0116928	4.11	0.026	.0107984	.0852217
x12	-.0484233	.0233486	-2.07	0.130	-.1227291	.0258825
_cons	-.3999868	.0264263	-15.14	0.001	-.4840872	-.3158864

. predict u3, r

. predict y3hat,xb

. reg lnb x8 x10 x12 l.u3,robust cluster(PD)

Linear regression

Number of obs =	2044
F( 2, 3) =	.
Prob > F =	.
R-squared =	0.1683
Root MSE =	.38784

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x8	.3595444	.0605114	5.94	0.010	.166697	.5521189
x10	.0230343	.0080001	2.88	0.064	-.0024255	.0484942
x12	-.0467371	.0236891	-1.97	0.143	-.1221265	.0286523
u3						
L1.	-.2083233	.0248749	-8.37	0.004	-.2874862	-.1291604
_cons	-.3923029	.0320769	-12.23	0.001	-.4943858	-.29022

. gen y32=y3hat\*y3hat

. gen y33=y32\*y3hat

. reg lnb x8 x10 x12 y32 y33, robust cluster(PD)

Linear regression

Number of obs =	2048
F( 2, 3) =	.
Prob > F =	.
R-squared =	0.2112
Root MSE =	.37745

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x8	-.1238481	.1334558	-0.93	0.422	-.5485639	.3008677
x10	-.021156	.0225796	-0.94	0.418	-.0930142	.0507023
x12	-.0032585	.0328675	-0.10	0.927	-.1078575	.1013404
y32	-2.440824	.0659538	-37.01	0.000	-2.650718	-2.230929
y33	5.594774	1.949199	2.87	0.064	-.6084468	11.798
_cons	.21764	.1475172	1.48	0.237	-.2518256	.6871056

. test y32 y33

( 1) y32 = 0

( 2) y33 = 0

F( 2, 3) = 695.50  
 Prob > F = 0.0001

. \*4 test actual variables snow

. reg lnb x14,robust cluster(PD)

Linear regression

Number of obs = 2048  
 F( 1, 3) = 31.12  
 Prob > F = 0.0114  
 R-squared = 0.0374  
 Root MSE = .41654

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x14	.0000177	3.18e-06	5.58	0.011	7.62e-06	.0000279
_cons	-.3566764	.0129127	-27.62	0.000	-.3977704	-.3155824

. predict u4,r

. predict y4hat,xb

. reg lnb x14 l.u4,robust cluster(PD)

Linear regression

Number of obs = 2044  
 F( 2, 3) = 41.33  
 Prob > F = 0.0066  
 R-squared = 0.0829  
 Root MSE = .40707

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x14	.0000146	2.68e-06	5.48	0.012	6.13e-06	.0000232
u4	-.2198725	.0251191	-8.75	0.003	-.2998127	-.1399323
_cons	-.3444738	.0144074	-23.91	0.000	-.3903246	-.298623

. gen y42=y4hat\*y4hat

. gen y43=y42\*y4hat

. reg lnb x14 y42 y43, robust cluster(PD)

Linear regression

Number of obs = 2048  
 F( 2, 3) = .  
 Prob > F = .  
 R-squared = 0.0931  
 Root MSE = .40452

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x14	-.0000499	.0000361	-1.38	0.260	-.0001646	.0000649
y42	-38.61231	13.13477	-2.94	0.061	-80.41302	3.188387
y43	-78.56115	24.3634	-3.22	0.048	-156.0964	-1.025931
_cons	1.12225	.7104486	1.58	0.212	-1.138714	3.383215

. test y42 y43

( 1) y42 = 0  
 ( 2) y43 = 0

F( 2, 3) = 5.27  
 Prob > F = 0.1044

. \*5 Test all seasonal variables

. reg lnb x1 x3 x5 x7 x9 x11 x13,robust cluster(PD)

Linear regression

Number of obs =	2048
F( 2, 3) =	.
Prob > F =	.
R-squared =	0.0685
Root MSE =	.41037

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	.1349615	.0237862	5.67	0.011	.0592633	.2106597
x3	-.2355102	.0426207	-5.53	0.012	-.3711482	-.0998721
x5	.1208904	.0226976	5.33	0.013	.0486564	.1931244
x7	-.1722566	.0263531	-6.54	0.007	-.2561238	-.0883895
x9	.0916431	.0056975	16.08	0.001	.0735111	.1097751
x11	-.0713794	.015176	-4.70	0.018	-.1196763	-.0230825
x13	-.0000633	.0000104	-6.06	0.009	-.0000966	-.0000301
_cons	-.3004035	.0037621	-79.85	0.000	-.3123762	-.2884307

. test x1 x3 x5

- ( 1) x1 = 0
- ( 2) x3 = 0
- ( 3) x5 = 0

F( 3, 3) = 104.26  
Prob > F = 0.0016

. test x7 x9 x11

- ( 1) x7 = 0
- ( 2) x9 = 0
- ( 3) x11 = 0

F( 3, 3) = 5067.02  
Prob > F = 0.0000

. predict u5,r

. predict y5hat,xb

. reg lnb x1 x3 x5 x7 x9 x11 x13 l.u5,robust cluster(PD)

Linear regression

Number of obs =	2044
F( 2, 3) =	.
Prob > F =	.
R-squared =	0.1798
Root MSE =	.38553

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	.0624769	.0132729	4.71	0.018	.0202366	.1047172
x3	-.1190887	.0255405	-4.66	0.019	-.2003701	-.0378074
x5	.0771844	.0173865	4.44	0.021	.0218527	.1325161
x7	-.1574476	.031236	-5.04	0.015	-.2568546	-.0580407
x9	.0058725	.0221515	0.27	0.808	-.0646235	.0763686
x11	-.0117633	.0021755	-5.41	0.012	-.0186866	-.00484
x13	-.0000411	7.48e-06	-5.50	0.012	-.000065	-.0000173
u5						
l1.	-.3465063	.0061496	-56.35	0.000	-.366077	-.3269356
_cons	-.3007566	.0051394	-58.52	0.000	-.3171125	-.2844008

```

. gen y52=y5hat*y5hat
.
. gen y53=y52*y5hat
.
. reg lnb x1 x3 x5 x7 x9 x11 x13 y52 y53, robust cluster(PD)
Linear regression                               Number of obs =    2048
                                                F( 2, 3) = .
                                                Prob > F = .
                                                R-squared = 0.0726
                                                Root MSE = 0.40967

```

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	-.3927736	.2604357	-1.51	0.229	-1.221596	.436049
x3	.696256	.4585303	1.52	0.226	-.7629919	2.155504
x5	-.3660672	.238717	-1.53	0.223	-1.125771	.3936368
x7	.453145	.3278496	1.38	0.261	-.5902186	1.496509
x9	-.1626285	.155874	-1.04	0.373	-.6586892	.3334323
x11	.1435013	.1158217	1.24	0.303	-.225095	.5120977
x13	.0001914	.0001258	1.52	0.226	-.0002091	.0005919
y52	-14.48724	7.383185	-1.96	0.145	-37.98383	9.009344
y53	-15.38288	7.837678	-1.96	0.144	-40.32587	9.560113
_cons	.5864203	.4509794	1.30	0.284	-.8487973	2.021638

```

. test y52 y53
( 1) y52 = 0
( 2) y53 = 0
      F( 2, 3) = 1.93
      Prob > F = 0.2897

```

. \*6 Test all seasonal variables reservoir level

. reg lnb x1 x3 x5,robust cluster(PD)

Linear regression Number of obs = 2048  
F( 2, 3) = .  
Prob > F = .  
R-squared = 0.0594  
Root MSE = .41196

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	.0033453	.0045847	0.73	0.518	-.0112452	.0179357
x3	.0519006	.0052004	9.98	0.002	.0353507	.0684505
x5	-.0494395	.0093035	-5.31	0.013	-.0790475	-.0198315
_cons	-.3080223	.003931	-78.36	0.000	-.3205324	-.2955121

. predict u6,r

. predict y6hat,xb

. reg lnb x1 x3 x5 l.u6,robust cluster(PD)

Linear regression Number of obs = 2044  
F( 2, 3) = .  
Prob > F = .  
R-squared = 0.1663  
Root MSE = .3883

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	.0054827	.0081235	0.67	0.548	-.0203698	.0313352
x3	.0491502	.0043839	11.21	0.002	.0351988	.0631016
x5	-.0492741	.0120941	-4.07	0.027	-.087763	-.0107852
u6						
L1.	-.3371873	.0045852	-73.54	0.000	-.3517794	-.3225952
_cons	-.306846	.0043574	-70.42	0.000	-.3207131	-.2929789

. gen y62=y6hat\*y6hat

. gen y63=y62\*y6hat

. reg lnb x1 x3 x5 y62 y63, robust cluster(PD)

Linear regression Number of obs = 2048  
F( 2, 3) = .  
Prob > F = .  
R-squared = 0.0655  
Root MSE = .41083

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	.0004191	.0016143	0.26	0.812	-.0047183	.0055565
x3	-.1939535	.0898036	-2.16	0.120	-.4797487	.0918418
x5	.1748859	.079359	2.20	0.115	-.0776698	.4274415
y62	-15.28364	5.881212	-2.60	0.080	-34.00028	3.433
y63	-15.41134	6.143785	-2.51	0.087	-34.9636	4.14093
_cons	.6753566	.3793388	1.78	0.173	-.5318688	1.882582

. test y62 y63

( 1) y62 = 0

( 2) y63 = 0

F( 2, 3) = 4.03  
Prob > F = 0.1412

. \*7 Test all seasonal variables inflow

. reg lnb x7 x9 x11,robust cluster(PD)

Linear regression

Number of obs = 2048  
 F( 2, 3) = .  
 Prob > F = .  
 R-squared = 0.0264  
 Root MSE = .41912

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x7	.798671	.1507637	5.30	0.013	.3188738	1.278468
x9	-.7372419	.1469909	-5.02	0.015	-1.205033	-.2694512
x11	.1648388	.0366748	4.49	0.021	.0481234	.2815543
_cons	-.2910538	.0068085	-42.75	0.000	-.3127216	-.269386

. predict u7,r

. predict y7hat,xb

. reg lnb x7 x9 x11 l.u7,robust cluster(PD)

Linear regression

Number of obs = 2044  
 F( 2, 3) = .  
 Prob > F = .  
 R-squared = 0.1182  
 Root MSE = .39934

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x7	.8729645	.1864942	4.68	0.018	.2794567	1.466472
x9	-.815294	.1898883	-4.29	0.023	-1.419603	-.2109847
x11	.1860477	.0531926	3.50	0.040	.0167652	.3553302
u7	-.307786	.0051634	-59.61	0.000	-.3242182	-.2913538
_cons	-.2898541	.0095619	-30.31	0.000	-.3202843	-.2594239

. gen y72=y7hat\*y7hat

. gen y73=y72\*y7hat

. reg lnb x7 x9 x11 y72 y73, robust cluster(PD)

Linear regression

Number of obs = 2048  
 F( 2, 3) = .  
 Prob > F = .  
 R-squared = 0.0341  
 Root MSE = .41768

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x7	-4.114254	.5312886	-7.74	0.004	-5.805051	-2.423457
x9	3.803617	.4860233	7.83	0.004	2.256874	5.350359
x11	-.8397121	.110125	-7.63	0.005	-1.190179	-.4892453
y72	-20.34572	2.689788	-7.56	0.005	-28.90582	-11.78561
y73	-19.54096	2.98893	-6.54	0.007	-29.05307	-10.02885
_cons	.9399545	.1573132	5.98	0.009	.4393137	1.440595

. test y72 y73

- ( 1) y72 = 0
- ( 2) y73 = 0

F( 2, 3) = 47.48  
 Prob > F = 0.0054



. \*8 Test all seasonal variables snow

. reg lnb x13,robust cluster(PD)

Linear regression Number of obs = 2048  
F( 1, 3) = 34.76  
Prob > F = 0.0097  
R-squared = 0.0389  
Root MSE = .41624

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x13	-.0000163	2.76e-06	-5.90	0.010	-.0000251	-7.49e-06
_cons	-.2055674	.0313771	-6.55	0.007	-.3054231	-.1057116

. predict u8,r

. predict y8hat,xb

. reg lnb x13 l.u8,robust cluster(PD)

Linear regression Number of obs = 2044  
F( 2, 3) = 1539.39  
Prob > F = 0.0000  
R-squared = 0.1314  
Root MSE = .39616

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x13	-.0000151	3.32e-06	-4.53	0.020	-.0000256	-4.48e-06
u8	-.3105743	.0082217	-37.78	0.000	-.3367394	-.2844093
_cons	-.2119107	.0396545	-5.34	0.013	-.3381089	-.0857124

. gen y82=y8hat\*y8hat

. gen y83=y82\*y8hat

. reg lnb x13 y82 y83, robust cluster(PD)

Linear regression Number of obs = 2048  
F( 2, 3) = .  
Prob > F = .  
R-squared = 0.0405  
Root MSE = .41609

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x13	-.0001519	.000175	-0.87	0.449	-.0007088	.0004049
y82	23.62875	32.41996	0.73	0.519	-79.54602	126.8035
y83	21.19482	30.72218	0.69	0.540	-76.57686	118.9665
_cons	-.9972056	1.111104	-0.90	0.436	-4.533234	2.538823

. test y82 y83

( 1) y82 = 0  
( 2) y83 = 0

F( 2, 3) = 0.56  
Prob > F = 0.6222

. \*9 test all actual and season variables

. reg lnb x1 x2 x3 x4 x5 x6 x7 x8 x9 x10 x11 x12 x13 x14,robust cluster(PD)

Linear regression

Number of obs =	2048
F( 2, 3) =	.
Prob > F =	.
R-squared =	0.4012
Root MSE =	.32958

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	.0257637	.00591	4.36	0.022	.0069554	.0445721
x2	.1326303	.0244628	5.42	0.012	.0547787	.210482
x3	-.1732826	.0340721	-5.09	0.015	-.2817151	-.0648501
x4	-.0998424	.0177273	-5.63	0.011	-.1562587	-.0434261
x5	.1162735	.0223337	5.21	0.014	.0451976	.1873494
x6	.0155678	.0030555	5.09	0.015	.0058438	.0252919
x7	.0397044	.0153937	2.58	0.082	-.0092852	.0886939
x8	.1649454	.032264	5.11	0.014	.062267	.2676238
x9	-.3089592	.0648347	-4.77	0.018	-.5152922	-.1026263
x10	.3107002	.0577739	5.38	0.013	.1268378	.4945626
x11	.1200419	.018848	6.37	0.008	.0600591	.1800247
x12	-.2702351	.0520206	-5.19	0.014	-.4357877	-.1046825
x13	-.0000869	.0000159	-5.47	0.012	-.0001375	-.0000364
x14	.0000395	8.05e-06	4.92	0.016	.0000139	.0000652
_cons	-.3024509	.0028606	-105.73	0.000	-.3115544	-.2933473

. test x1 x2 x3 x4 x5 x6

( 1) x1 = 0  
 ( 2) x2 = 0  
 ( 3) x3 = 0  
 ( 4) x4 = 0  
 ( 5) x5 = 0  
 ( 6) x6 = 0  
 Constraint 4 dropped  
 Constraint 5 dropped  
 Constraint 6 dropped  
 F( 3, 3) = 22.98  
 Prob > F = 0.0143

. test x1 x3 x5

( 1) x1 = 0  
 ( 2) x3 = 0  
 ( 3) x5 = 0  
 F( 3, 3) = 56.54  
 Prob > F = 0.0039

. test x2 x3 x5

( 1) x2 = 0  
 ( 2) x3 = 0  
 ( 3) x5 = 0  
 F( 3, 3) = 13.17  
 Prob > F = 0.0311

. test x7 x8 x9 x10 x11 x12

( 1) x7 = 0  
 ( 2) x8 = 0  
 ( 3) x9 = 0  
 ( 4) x10 = 0  
 ( 5) x11 = 0  
 ( 6) x12 = 0  
 Constraint 4 dropped  
 Constraint 5 dropped  
 Constraint 6 dropped  
 F( 3, 3) = 9.30  
 Prob > F = 0.0498

. test x7 x9 x11

( 1) x7 = 0  
 ( 2) x9 = 0  
 ( 3) x11 = 0  
 F( 3, 3) = 888.32  
 Prob > F = 0.0001

. test x8 x10 x12

```

. predict u9,r
.
. predict y9hat,xb
.
. reg lnb x1 x2 x3 x4 x5 x6 x7 x8 x9 x10 x11 x12 x13 x14 l.u9,robust cluster(PD)

```

Linear regression

Number of obs =	2044
F( 2, 3) =	.
Prob > F =	.
R-squared =	0.4262
Root MSE =	.32302

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	.0014108	.0036564	0.39	0.725	-.0102256	.0130471
x2	.1329635	.0234429	5.67	0.011	.0583578	.2075692
x3	-.1316029	.0197577	-6.66	0.007	-.1944808	-.0687251
x4	-.1017496	.0182071	-5.59	0.011	-.1596928	-.0438064
x5	.1016956	.0168103	6.05	0.009	.0481979	.1551934
x6	.0141528	.002072	6.83	0.006	.0075589	.0207468
x7	.0023869	.0125666	0.19	0.861	-.0376056	.0423795
x8	.1934579	.0453652	4.26	0.024	.0490857	.3378301
x9	-.3021122	.0613671	-4.92	0.016	-.4974097	-.1068148
x10	.2904838	.0432297	6.72	0.007	.1529077	.42806
x11	.1224012	.0204784	5.98	0.009	.0572298	.1875726
x12	-.2522657	.0394765	-6.39	0.008	-.3778977	-.1266338
x13	-.0000767	.0000119	-6.43	0.008	-.0001147	-.0000387
x14	.0000361	6.26e-06	5.77	0.010	.0000162	.0000561
u9						
_L1.	-.2083604	.0473865	-4.40	0.022	-.3591653	-.0575554
_cons	-.3019874	.0037358	-80.84	0.000	-.3138763	-.2900985

```

. gen y92=y9hat*y9hat
.
. gen y93=y92*y9hat
.
. reg lnb x1 x2 x3 x4 x5 x6 x7 x8 x9 x10 x11 x12 x13 x14 y92 y93, robust cluster(> PD)

```

Linear regression

Number of obs =	2048
F( 2, 3) =	.
Prob > F =	.
R-squared =	0.4482
Root MSE =	.31656

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	-.0021368	.0028591	-0.75	0.509	-.0112357	.006962
x2	.1256931	.0175977	7.14	0.006	.0696894	.1816968
x3	-.0862545	.0149531	-5.77	0.010	-.133842	-.0386669
x4	-.1030734	.0145496	-7.08	0.006	-.1493767	-.0567701
x5	.0669915	.0116549	5.75	0.010	.0299003	.1040826
x6	.0094184	.0025893	3.64	0.036	.0011782	.0176586
x7	-.016136	.0072015	-2.24	0.111	-.0390543	.0067823
x8	.2671832	.0437816	6.10	0.009	.1278505	.4065159
x9	-.294002	.060112	-4.89	0.016	-.4853052	-.1026988
x10	.3244323	.0479684	6.76	0.007	.1717756	.477089
x11	.1317969	.0183329	7.19	0.006	.0734533	.1901404
x12	-.2809667	.045352	-6.20	0.008	-.4252969	-.1366365
x13	-.0000621	9.49e-06	-6.54	0.007	-.0000923	-.0000319
x14	.0000371	6.14e-06	6.05	0.009	.0000176	.0000567
y92	-1.048833	.3714383	-2.82	0.067	-2.230915	.1332497
y93	-1.092395	.4342612	-2.52	0.087	-2.474408	.289618
_cons	-.2514322	.020783	-12.10	0.001	-.317573	-.1852915

```

. test y92 y93

```

- ( 1) y92 = 0
- ( 2) y93 = 0

F( 2, 3) = 4.24  
 Prob > F = 0.1337

. \*10 test all actual and season variables reservoir level

. reg lnb x1 x2 x3 x4 x5 x6,robust cluster(PD)

Linear regression

Number of obs =	2048
F( 2, 3) =	.
Prob > F =	.
R-squared =	0.2079
Root MSE =	.37833

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	-.0935043	.013991	-6.68	0.007	-.1380299	-.0489786
x2	.096312	.0175658	5.48	0.012	.0404098	.1522141
x3	.1620522	.0262535	6.17	0.009	.0785018	.2456026
x4	-.1080665	.0197344	-5.48	0.012	-.17087	-.045263
x5	-.1033579	.0196916	-5.25	0.013	-.1660252	-.0406905
x6	.062402	.0118791	5.25	0.013	.0245974	.1002066
_cons	-.3109087	.0054749	-56.79	0.000	-.3283323	-.2934851

. test x1 x3 x5

- ( 1) x1 = 0
- ( 2) x3 = 0
- ( 3) x5 = 0

F( 3, 3) = 2227.59  
 Prob > F = 0.0000

. test x2 x4 x6

- ( 1) x2 = 0
- ( 2) x4 = 0
- ( 3) x6 = 0

F( 3, 3) = 592.35  
 Prob > F = 0.0001

. predict u10,r

. predict y10hat,xb

. reg lnb x1 x2 x3 x4 x5 x6 l.u10,robust cluster(PD)

Linear regression

Number of obs =	2044
F( 2, 3) =	.
Prob > F =	.
R-squared =	0.2646
Root MSE =	.36495

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	-.0835084	.0081056	-10.30	0.002	-.1093041	-.0577128
x2	.0917716	.0165617	5.54	0.012	.0390648	.1444784
x3	.1509043	.0222966	6.77	0.007	.0799467	.2218619
x4	-.104771	.0189336	-5.53	0.012	-.1650261	-.0445159
x5	-.1000901	.0205618	-4.87	0.017	-.1655271	-.0346532
x6	.0602532	.0104681	5.76	0.010	.026939	.0935674
u10						
l1.	-.2684024	.019691	-13.63	0.001	-.3310679	-.2057368
_cons	-.3103394	.0063298	-49.03	0.000	-.3304835	-.2901953

```

. gen y102=y10hat*y10hat
.
. gen y103=y102*y10hat
.
. reg lnb x1 x2 x3 x4 x5 x6 y102 y103, robust cluster(PD)
Linear regression                               Number of obs =   2048
                                                F( 2, 3) = .
                                                Prob > F = .
                                                R-squared = 0.2545
                                                Root MSE = 0.3672

```

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	-.0642161	.0112217	-5.72	0.011	-.0999286	-.0285036
x2	.0660077	.0092185	7.16	0.006	.0366703	.0953452
x3	.1316867	.0185468	7.10	0.006	.0726626	.1907108
x4	-.084035	.01109	-7.58	0.005	-.1193283	-.0487417
x5	-.0990379	.0109169	-9.07	0.003	-.1337803	-.0642956
x6	.0591676	.0069447	8.52	0.003	.0370664	.0812689
y102	-3.838924	1.096009	-3.50	0.039	-7.326913	-.3509346
y103	-5.53957	1.398987	-3.96	0.029	-9.991771	-1.087368
_cons	-.1089166	.0675566	-1.61	0.205	-.3239119	.1060786

```

. test y102 y103
( 1) y102 = 0
( 2) y103 = 0
      F( 2, 3) = 104.83
      Prob > F = 0.0017
.

```

. \*11 test all actual and season variables inflow

. reg lnb x7 x8 x9 x10 x11 x12,robust cluster(PD)

Linear regression Number of obs = **2048**  
 F( 2, 3) = .  
 Prob > F = .  
 R-squared = **0.1796**  
 Root MSE = **.38503**

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x7	.1960575	.0603962	3.25	0.048	.0038498	.3882651
x8	.3703396	.0704633	5.26	0.013	.1460939	.5945853
x9	-.2896184	.0585253	-4.95	0.016	-.4758721	-.1033646
x10	.0593038	.0080752	7.34	0.005	.0336049	.0850028
x11	-.0128024	.0297366	-0.43	0.696	-.1074374	.0818326
x12	-.0073843	.0053045	-1.39	0.258	-.0242658	.0094971
_cons	-.3348426	.0165653	-20.21	0.000	-.3875608	-.2821243

. test x7 x9 x11

- ( 1) x7 = 0
- ( 2) x9 = 0
- ( 3) x11 = 0

F( 3, 3) = **1089.48**  
 Prob > F = **0.0000**

. test x8 x10 x12

- ( 1) x8 = 0
- ( 2) x10 = 0
- ( 3) x12 = 0

F( 3, 3) = **18.58**  
 Prob > F = **0.0193**

. predict u11,r

. predict y11hat,xb

. reg lnb x7 x8 x9 x10 x11 x12 l.u11,robust cluster(PD)

Linear regression Number of obs = **2044**  
 F( 2, 3) = .  
 Prob > F = .  
 R-squared = **0.2327**  
 Root MSE = **.37279**

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x7	.182583	.0639043	2.86	0.065	-.020789	.385955
x8	.4027667	.0752218	5.35	0.013	.1633775	.642156
x9	-.2758293	.0756636	-3.65	0.036	-.5166247	-.0350338
x10	.0269328	.0057649	4.67	0.019	.0085864	.0452793
x11	-.0286082	.0263039	-1.09	0.356	-.1123192	.0551027
x12	-.0014737	.009273	-0.16	0.884	-.0309846	.0280372
u11						
l1.	-.2561999	.0244042	-10.50	0.002	-.333865	-.1785348
_cons	-.3264909	.0179116	-18.23	0.000	-.3834937	-.2694881

```

. gen y112=y11hat*y11hat
.
. gen y113=y112*y11hat
.
. reg lnb x7 x8 x9 x10 x11 x12 y112 y113, robust cluster(PD)
Linear regression                               Number of obs =    2048
                                                F( 2, 3) = .
                                                Prob > F = .
                                                R-squared = 0.2221
                                                Root MSE = 0.3751

```

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x7	-.0083847	.0995324	-0.08	0.938	-.3251413	.3083719
x8	.2263687	.0264406	8.56	0.003	.1422228	.3105146
x9	-.0213408	.0884904	-0.24	0.825	-.3029567	.2602751
x10	.0654279	.0112983	5.79	0.010	.0294717	.1013842
x11	-.0037408	.0423211	-0.09	0.935	-.1384254	.1309438
x12	-.01235	.0051053	-2.42	0.094	-.0285974	.0038975
y112	-1.571287	.4985058	-3.15	0.051	-3.157755	.015181
y113	-.545712	.1362655	-4.00	0.028	-.9793695	-.1120545
_cons	-.211145	.0606466	-3.48	0.040	-.4041497	-.0181403

```

. test y112 y113
( 1) y112 = 0
( 2) y113 = 0
      F( 2, 3) = 8.71
      Prob > F = 0.0563

```

. \*12 test all actual and season variables snow

. reg lnb x13 x14,robust cluster(PD)

Linear regression Number of obs = 2048  
F( 2, 3) = 40.63  
Prob > F = 0.0067  
R-squared = 0.1133  
Root MSE = .39989

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x13	-.0000241	3.44e-06	-7.00	0.006	-.000035	-.0000131
x14	.0000265	4.91e-06	5.39	0.012	.0000108	.0000421
_cons	-.2768166	.0125432	-22.07	0.000	-.3167347	-.2368985

. predict u12,r

. predict y12hat,xb

. reg lnb x13 x14 l.u12,robust cluster(PD)

Linear regression Number of obs = 2044  
F( 2, 3) = .  
Prob > F = .  
R-squared = 0.1744  
Root MSE = .38633

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x13	-.0000217	3.47e-06	-6.24	0.008	-.0000327	-.0000106
x14	.0000242	4.42e-06	5.47	0.012	.0000101	.0000382
u12	-.263631	.0142656	-18.48	0.000	-.3090305	-.2182315
_cons	-.2794965	.0131618	-21.24	0.000	-.3213832	-.2376097

. gen y122=y12hat\*y12hat

. gen y123=y122\*y12hat

. reg lnb x13 x14 y122 y123, robust cluster(PD)

Linear regression Number of obs = 2048  
F( 2, 3) = .  
Prob > F = .  
R-squared = 0.1263  
Root MSE = .39715

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x13	-8.77e-06	7.69e-07	-11.41	0.001	-.0000112	-6.33e-06
x14	.000016	2.86e-06	5.61	0.011	6.95e-06	.0000251
y122	.0321644	1.113251	0.03	0.979	-3.510697	3.575026
y123	1.913976	1.562699	1.22	0.308	-3.059229	6.887181
_cons	-.2376768	.0367979	-6.46	0.008	-.3547841	-.1205696

. test y122 y123

( 1) y122 = 0  
( 2) y123 = 0

F( 2, 3) = 14.77  
Prob > F = 0.0280



```
. reg lnb x15 x16 x17 x18 x19 x20 x21,robust cluster(PD)
```

Linear regression

Number of obs = 2048  
 $F(2, 3) = .$   
 Prob > F = .  
 R-squared = 0.3591  
 Root MSE = .3404

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x15	.1221162	.0208742	5.85	0.010	.0556852	.1885471
x16	-.0856981	.0136696	-6.27	0.008	-.1292008	-.0421954
x17	-.0008239	.0021173	-0.39	0.723	-.0075622	.0059144
x18	.1855929	.0383689	4.84	0.017	.0634858	.3076999
x19	.2433594	.0427062	5.70	0.011	.1074492	.3792695
x20	-.1866711	.0302139	-6.18	0.009	-.2828252	-.0905171
x21	.0000379	6.81e-06	5.56	0.011	.0000162	.0000595
_cons	-.1569379	.0323751	-4.85	0.017	-.25997	-.0539058

```
. test x15 x16 x17
```

- ( 1) x15 = 0
- ( 2) x16 = 0
- ( 3) x17 = 0

$F(3, 3) = 393.94$   
 Prob > F = 0.0002

```
. test x18 x19 x20
```

- ( 1) x18 = 0
- ( 2) x19 = 0
- ( 3) x20 = 0

$F(3, 3) = 463.31$   
 Prob > F = 0.0002

```
. predict u13,r
```

```
. predict y13hat,xb
```

```
. reg lnb x15 x16 x17 x18 x19 x20 x21 l.u13,robust cluster(PD)
```

Linear regression

Number of obs = 2044  
 $F(2, 3) = .$   
 Prob > F = .  
 R-squared = 0.3768  
 Root MSE = .33604

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x15	.1197471	.0194632	6.15	0.009	.0578066	.1816875
x16	-.0860069	.0143155	-6.01	0.009	-.1315651	-.0404486
x17	-.002768	.0027949	-0.99	0.395	-.0116627	.0061267
x18	.2169872	.0549286	3.95	0.029	.0421799	.3917945
x19	.2195866	.0345406	6.36	0.008	.1096629	.3295104
x20	-.1690278	.0230589	-7.33	0.005	-.2424114	-.0956442
x21	.0000346	5.07e-06	6.83	0.006	.0000185	.0000508
u13						
l1.	-.1709837	.0441453	-3.87	0.030	-.3114738	-.0304935
_cons	-.1615119	.0401189	-4.03	0.028	-.2891881	-.0338357

```

. gen y132=y13hat*y13hat
.
. gen y133=y132*y13hat
.
. reg lnb x15 x16 x17 x18 x19 x20 x21 y132 y133, robust cluster(PD)
Linear regression                               Number of obs =   2048
                                                F( 2,          3) =    .
                                                Prob > F       =    .
                                                R-squared     =  0.3911
                                                Root MSE     =  0.33196

```

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x15	.1260709	.0264422	4.77	0.018	.04192	.2102217
x16	-.0939336	.0183048	-5.13	0.014	-.1521875	-.0356797
x17	.000757	.0011847	0.64	0.568	-.0030131	.0045271
x18	.2465286	.0595046	4.14	0.026	.0571584	.4358988
x19	.275239	.057596	4.78	0.017	.0919429	.458535
x20	-.2080563	.0439796	-4.73	0.018	-.3480189	-.0680937
x21	.0000404	9.37e-06	4.31	0.023	.0000106	.0000702
y132	-.9331397	.306123	-3.05	0.056	-1.90736	.0410805
y133	-1.267408	.5587959	-2.27	0.108	-3.045745	.5109304
_cons	-.1127396	.0422725	-2.67	0.076	-.2472697	.0217904

```

. test y132 y133
( 1) y132 = 0
( 2) y133 = 0
      F( 2,          3) =    4.80
      Prob > F =    0.1162

```

. \*14 Test diff. variables reservoir level

. reg lnb x15 x16 x17,robust cluster(PD)

Linear regression

Number of obs =	2048
F( 2, 3) =	.
Prob > F =	.
R-squared =	0.1461
Root MSE =	.39252

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x15	.0725946	.0116414	6.24	0.008	.0355465	.1096426
x16	-.1131884	.0182868	-6.19	0.008	-.1713852	-.0549916
x17	.0745172	.0135657	5.49	0.012	.0313452	.1176892
_cons	-.2088794	.0201347	-10.37	0.002	-.2729569	-.144802

. predict u14,r

. predict y14hat,xb

. reg lnb x15 x16 x17 l.u14,robust cluster(PD)

Linear regression

Number of obs =	2044
F( 2, 3) =	.
Prob > F =	.
R-squared =	0.1851
Root MSE =	.3839

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x15	.0614928	.0091056	6.75	0.007	.0325146	.090471
x16	-.1058456	.0162642	-6.51	0.007	-.1576055	-.0540858
x17	.0754924	.0134893	5.60	0.011	.0325632	.1184215
u14						
l1.	-.2170343	.0265641	-8.17	0.004	-.3015731	-.1324955
_cons	-.2143466	.0258678	-8.29	0.004	-.2966693	-.1320238

. gen y142=y14hat\*y14hat

. gen y143=y142\*y14hat

. reg lnb x15 x16 x17 y142 y143, robust cluster(PD)

Linear regression

Number of obs =	2048
F( 2, 3) =	.
Prob > F =	.
R-squared =	0.1612
Root MSE =	.38923

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x15	.07786	.0113629	6.85	0.006	.0416981	.114022
x16	-.1282917	.0205025	-6.26	0.008	-.1935398	-.0630436
x17	.089163	.0162532	5.49	0.012	.037438	.1408881
y142	-1.48191	.5964136	-2.48	0.089	-3.379965	.4161439
y143	-2.983901	1.281937	-2.33	0.102	-7.063596	1.095794
_cons	-.1720526	.0247978	-6.94	0.006	-.2509702	-.0931349

. test y142 y143

( 1) y142 = 0

( 2) y143 = 0

F( 2, 3) =	3.14
Prob > F =	0.1841

. \*15 Test diff. variables inflow

. reg lnb x18 x19 x20,robust cluster(PD)

Linear regression

Number of obs =	2048
F( 2, 3) =	.
Prob > F =	.
R-squared =	0.1350
Root MSE =	.39506

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x18	.2767831	.053038	5.22	0.014	.1079926	.4455736
x19	-.0110043	.0041471	-2.65	0.077	-.0242021	.0021935
x20	.0778899	.0153442	5.08	0.015	.0290578	.126722
_cons	-.2446413	.011143	-21.95	0.000	-.2801032	-.2091794

. predict u15,r

. predict y15hat,xb

. reg lnb x18 x19 x20 l.u15,robust cluster(PD)

Linear regression

Number of obs =	2044
F( 2, 3) =	.
Prob > F =	.
R-squared =	0.1833
Root MSE =	.38432

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x18	.2926945	.0577427	5.07	0.015	.1089313	.4764576
x19	-.0439787	.0090206	-4.88	0.016	-.0726862	-.0152712
x20	.1031069	.0202263	5.10	0.015	.0387378	.167476
u15						
l1.	-.2374937	.0308367	-7.70	0.005	-.3356299	-.1393575
_cons	-.2445249	.0147172	-16.61	0.000	-.2913615	-.1976882

. gen y152=y15hat\*y15hat

. gen y153=y152\*y15hat

. reg lnb x15 x16 x17 y152 y153, robust cluster(PD)

Linear regression

Number of obs =	2048
F( 2, 3) =	.
Prob > F =	.
R-squared =	0.2545
Root MSE =	.36694

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x15	.1013253	.0192029	5.28	0.013	.040213	.1624376
x16	-.11897	.0180921	-6.58	0.007	-.1765473	-.0613927
x17	.0216023	.0038429	5.62	0.011	.0093725	.0338321
y152	-3.551176	1.401365	-2.53	0.085	-8.010945	.908593
y153	-2.827913	1.641931	-1.72	0.183	-8.05327	2.397444
_cons	.0112885	.0543659	0.21	0.849	-.1617279	.1843049

. test y152 y153

- ( 1) y152 = 0
- ( 2) y153 = 0

F( 2, 3) = 29.88  
 Prob > F = 0.0105

. \*16 Test diff. variables snow

. reg lnb x21,robust cluster(PD)

Linear regression

Number of obs = 2048  
 F( 1, 3) = 39.01  
 Prob > F = 0.0083  
 R-squared = 0.1128  
 Root MSE = .39991

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x21	.0000251	4.01e-06	6.25	0.008	.0000123	.0000379
_cons	-.2661994	.0078721	-33.82	0.000	-.291252	-.2411468

. predict u16,r

. predict y16hat,xb

. reg lnb x21 l.u16,robust cluster(PD)

Linear regression

Number of obs = 2044  
 F( 2, 3) = 573.60  
 Prob > F = 0.0001  
 R-squared = 0.1754  
 Root MSE = .38598

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x21	.0000226	3.81e-06	5.92	0.010	.0000104	.0000347
u16						
l1.	-.2672374	.0128813	-20.75	0.000	-.3082313	-.2262434
_cons	-.2686156	.0100604	-26.70	0.000	-.3006322	-.2365989

. gen y162=y16hat\*y16hat

. gen y163=y162\*y16hat

. reg lnb x21 y162 y163, robust cluster(PD)

Linear regression

Number of obs = 2048  
 F( 2, 3) = .  
 Prob > F = .  
 R-squared = 0.1224  
 Root MSE = .39794

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x21	.0000163	3.22e-06	5.06	0.015	6.04e-06	.0000266
y162	.4800278	1.173451	0.41	0.710	-3.254417	4.214473
y163	2.001166	1.854963	1.08	0.360	-3.902153	7.904485
_cons	-.243366	.0351227	-6.93	0.006	-.355142	-.13159

. test y162 y163

( 1) y162 = 0

( 2) y163 = 0

F( 2, 3) = 8.08  
 Prob > F = 0.0619

. \*17 test all actual variables and diff. variables

. reg lnb x2 x4 x6 x8 x10 x12 x14 x15 x16 x17 x18 x19 x20 x21,robust cluster(PD)

Linear regression

Number of obs =	2048
F( 2, 3) =	.
Prob > F =	.
R-squared =	0.4012
Root MSE =	.32958

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	.1576444	.0296668	5.31	0.013	.0632313	.2520575
x4	-.2718131	.0516523	-5.26	0.013	-.4361939	-.1074323
x6	.1312636	.0252004	5.21	0.014	.0510647	.2114626
x8	.2051387	.0442825	4.63	0.019	.0642119	.3460655
x10	.0007585	.0119692	0.06	0.953	-.037333	.03885
x12	-.1496097	.0333627	-4.48	0.021	-.2557848	-.0434347
x14	-.0000471	7.85e-06	-6.00	0.009	-.0000721	-.0000221
x15	-.0249957	.0058611	-4.26	0.024	-.0436483	-.006343
x16	.1719626	.0340132	5.06	0.015	.0637175	.2802077
x17	-.1157132	.0222993	-5.19	0.014	-.1866795	-.0447469
x18	-.0401698	.0154063	-2.61	0.080	-.0891995	.0088598
x19	.3099386	.0647876	4.78	0.017	.1037554	.5161218
x20	-.1205958	.0188368	-6.40	0.008	-.1805428	-.0606488
x21	.0000867	.0000159	5.46	0.012	.0000361	.0001372
_cons	-.3024536	.00286	-105.75	0.000	-.3115552	-.2933519

. test x2 x4 x6 x15 x16 x17

( 1) x2 = 0  
 ( 2) x4 = 0  
 ( 3) x6 = 0  
 ( 4) x15 = 0  
 ( 5) x16 = 0  
 ( 6) x17 = 0  
 Constraint 1 dropped  
 Constraint 5 dropped  
 Constraint 6 dropped  
 F( 3, 3) = 12.12  
 Prob > F = 0.0349

. test x2 x4 x6

( 1) x2 = 0  
 ( 2) x4 = 0  
 ( 3) x6 = 0  
 F( 3, 3) = 19.10  
 Prob > F = 0.0186

. test x15 x16 x17

( 1) x15 = 0  
 ( 2) x16 = 0  
 ( 3) x17 = 0  
 F( 3, 3) = 57.96  
 Prob > F = 0.0037

. test x8 x10 x12 x18 x19 x20

( 1) x8 = 0  
 ( 2) x10 = 0  
 ( 3) x12 = 0  
 ( 4) x18 = 0  
 ( 5) x19 = 0  
 ( 6) x20 = 0  
 Constraint 2 dropped  
 Constraint 3 dropped  
 Constraint 6 dropped  
 F( 3, 3) = 9.24  
 Prob > F = 0.0503

. test x8 x10 x12

( 1) x8 = 0  
 ( 2) x10 = 0  
 ( 3) x12 = 0  
 F( 3, 3) = 35.15  
 Prob > F = 0.0077

. test x18 x19 x20

```

. predict u17,r
.
. predict y17hat,xb
.
. reg lnb x2 x4 x6 x8 x10 x12 x14 x15 x16 x17 x18 x19 x20 x21 l.u17,robust cluste
> r(PD)

```

Linear regression

Number of obs =	2044
F( 2, 3) =	.
Prob > F =	.
R-squared =	0.4262
Root MSE =	.32302

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	.1335124	.0222798	5.99	0.009	.062608	.2044167
x4	-.231879	.0376392	-6.16	0.009	-.3516637	-.1120944
x6	.1152252	.0186797	6.17	0.009	.0557782	.1746722
x8	.1964446	.0364991	5.38	0.013	.0802883	.3126009
x10	-.0128382	.0209517	-0.61	0.583	-.0795159	.0538395
x12	-.1291887	.0193143	-6.69	0.007	-.1906554	-.0677219
x14	-.0000402	5.68e-06	-7.08	0.006	-.0000583	-.0000222
x15	-.0005324	.0036639	-0.15	0.894	-.0121927	.0111278
x16	.130125	.0196907	6.61	0.007	.0674602	.1927897
x17	-.1010887	.0167726	-6.03	0.009	-.1544667	-.0477108
x18	-.0029631	.0126208	-0.23	0.829	-.0431282	.0372021
x19	.3033135	.0613727	4.94	0.016	.1079981	.4986289
x20	-.1230493	.0204884	-6.01	0.009	-.1882525	-.0578462
x21	.0000764	.0000119	6.41	0.008	.0000385	.0001143
u17						
l1.	-.2083652	.047385	-4.40	0.022	-.3591656	-.0575649
_cons	-.3019897	.0037349	-80.86	0.000	-.3138759	-.2901034

```

. gen y172=y17hat*y17hat
.
. gen y173=y172*y17hat
.
. reg lnb x2 x4 x6 x8 x10 x12 x14 x15 x16 x17 x18 x19 x20 x21 y172 y173, robust c
> luster(PD)

```

Linear regression

Number of obs =	2048
F( 3, 3) =	.
Prob > F =	.
R-squared =	0.4481
Root MSE =	.31656

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	.1235208	.017173	7.19	0.006	.0688686	.178173
x4	-.1891657	.0293378	-6.45	0.008	-.2825319	-.0957996
x6	.0762674	.0140128	5.44	0.012	.0316725	.1208624
x8	.2509354	.0473713	5.30	0.013	.1001787	.4016922
x10	.0306547	.0167957	1.83	0.165	-.0227967	.0841062
x12	-.149208	.0280033	-5.33	0.013	-.238327	-.060089
x14	-.0000249	3.67e-06	-6.78	0.007	-.0000366	-.0000132
x15	.0021922	.0027931	0.78	0.490	-.0066968	.0110812
x16	.0860796	.014977	5.75	0.010	.0384162	.133743
x17	-.0668578	.0116495	-5.74	0.011	-.1039318	-.0297838
x18	.0162522	.0072767	2.23	0.112	-.0069055	.0394099
x19	.2938111	.0600107	4.90	0.016	.1028302	.4847919
x20	-.1317552	.0182992	-7.20	0.006	-.1899914	-.073519
x21	.000062	9.49e-06	6.53	0.007	.0000318	.0000922
y172	-1.048524	.3713334	-2.82	0.067	-2.230272	.133225
y173	-1.092193	.4341727	-2.52	0.087	-2.473924	.2895384
_cons	-.2514534	.0207767	-12.10	0.001	-.3175743	-.1853325

```

. test y172 y173
( 1) y172 = 0
( 2) y173 = 0
F( 2, 3) = 4.24
Prob > F = 0.1337

```

. \*18 test all actual variables and diff. variables reservoir level

. reg lnb x2 x4 x6 x15 x16 x17,robust cluster(PD)

Linear regression Number of obs = 2048  
F( 2, 3) = .  
Prob > F = .  
R-squared = 0.2079  
Root MSE = .37833

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	.0027908	.0036874	0.76	0.504	-.0089441	.0145258
x4	.0540046	.0065837	8.20	0.004	.0330524	.0749568
x6	-.0409559	.0078252	-5.23	0.014	-.0658593	-.0160525
x15	.0935151	.0139895	6.68	0.007	.0489943	.138036
x16	-.1620661	.0262537	-6.17	0.009	-.2456169	-.0785152
x17	.1033639	.0196935	5.25	0.013	.0406903	.1660374
_cons	-.3109053	.0054731	-56.81	0.000	-.328323	-.2934876

. test x2 x4 x6

- ( 1) x2 = 0
- ( 2) x4 = 0
- ( 3) x6 = 0

F( 3, 3) = 29434.46  
Prob > F = 0.0000

. test x15 x16 x17

- ( 1) x15 = 0
- ( 2) x16 = 0
- ( 3) x17 = 0

F( 3, 3) = 2223.74  
Prob > F = 0.0000

. predict u18,r

. predict y18hat,xb

. reg lnb x2 x4 x6 x15 x16 x17 l.u18,robust cluster(PD)

Linear regression Number of obs = 2044  
F( 2, 3) = .  
Prob > F = .  
R-squared = 0.2647  
Root MSE = .36495

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	.0082453	.0085123	0.97	0.404	-.0188447	.0353353
x4	.0461537	.0035079	13.16	0.001	.0349899	.0573176
x6	-.0398374	.0101076	-3.94	0.029	-.0720043	-.0076705
x15	.0835214	.0081048	10.31	0.002	.0577282	.1093146
x16	-.1509204	.0222974	-6.77	0.007	-.2218807	-.0799601
x17	.1000968	.0205638	4.87	0.017	.0346536	.1655401
u18						
l1.	-.2684067	.0196914	-13.63	0.001	-.3310736	-.2057398
_cons	-.3103346	.0063263	-49.05	0.000	-.3304677	-.2902014



```

. gen y182=y18hat*y18hat
.
. gen y183=y182*y18hat
.
. reg lnb x2 x4 x6 x15 x16 x17 y182 y183, robust cluster(PD)
Linear regression                               Number of obs =    2048
                                                F( 2,          3) =    .
                                                Prob > F       =    .
                                                R-squared     =    0.2545
                                                Root MSE     =    .36721

```

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	.0018018	.0025016	0.72	0.523	-.0061593	.0097628
x4	.0476273	.0076308	6.24	0.008	.0233426	.071912
x6	-.0398543	.0039935	-9.98	0.002	-.0525635	-.027145
x15	.0641981	.011226	5.72	0.011	.0284721	.0999241
x16	-.1316539	.0185483	-7.10	0.006	-.1906829	-.0726249
x17	.0990171	.0109146	9.07	0.003	.064282	.1337522
y182	-3.837704	1.095996	-3.50	0.039	-7.325653	-.3497551
y183	-5.537071	1.398808	-3.96	0.029	-9.988703	-1.085439
_cons	-.1089701	.0675575	-1.61	0.205	-.3239682	.1060281

```

. test y182 y183
( 1) y182 = 0
( 2) y183 = 0
      F( 2,          3) =    105.11
      Prob > F       =    0.0017

```

. \*19 test all actual variables and diff. variables inflow

. reg lnb x8 x10 x12 x18 x19 x20,robust cluster(PD)

Linear regression Number of obs = **2048**  
 F( 2, 3) = .  
 Prob > F = .  
 R-squared = **0.1796**  
 Root MSE = **.38503**

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x8	.566397	.0894224	6.33	0.008	.281815	.8509789
x10	-.2303144	.0584281	-3.94	0.029	-.4162587	-.0443702
x12	-.0201868	.0328806	-0.61	0.583	-.1248276	.0844541
x18	-.1960574	.0603961	-3.25	0.048	-.3882648	-.00385
x19	.2896183	.0585253	4.95	0.016	.1033648	.4758718
x20	.0128024	.0297366	0.43	0.696	-.0818326	.1074374
_cons	-.3348425	.0165653	-20.21	0.000	-.3875608	-.2821243

. test x8 x10 x12

( 1) **x8 = 0**  
 ( 2) **x10 = 0**  
 ( 3) **x12 = 0**

F( 3, 3) = **125.37**  
 Prob > F = **0.0012**

. test x18 x19 x20

( 1) **x18 = 0**  
 ( 2) **x19 = 0**  
 ( 3) **x20 = 0**

F( 3, 3) = **1089.49**  
 Prob > F = **0.0000**

. predict u19,r

. predict y19hat,xb

. reg lnb x8 x10 x12 x18 x19 x20 l.u19,robust cluster(PD)

Linear regression Number of obs = **2044**  
 F( 2, 3) = .  
 Prob > F = .  
 R-squared = **0.2327**  
 Root MSE = **.37279**

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x8	.5853496	.1118959	5.23	0.014	.2292469	.9414524
x10	-.2488963	.079435	-3.13	0.052	-.5016938	.0039011
x12	-.030082	.030266	-0.99	0.394	-.1264019	.0662379
x18	-.1825829	.0639042	-2.86	0.065	-.3859546	.0207888
x19	.2758291	.0756635	3.65	0.036	.035034	.5166243
x20	.0286083	.0263039	1.09	0.356	-.0551025	.1123191
u19						
l1.	-.2561999	.0244042	-10.50	0.002	-.333865	-.1785348
_cons	-.3264909	.0179116	-18.23	0.000	-.3834937	-.2694881

```

. gen y192=y19hat*y19hat
.
. gen y193=y192*y19hat
.
. reg lnb x8 x10 x12 x18 x19 x20 y192 y193, robust cluster(PD)
Linear regression                               Number of obs =    2048
                                                F( 2, 3) = .
                                                Prob > F = .
                                                R-squared = 0.2221
                                                Root MSE = 0.3751

```

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x8	.217984	.0961315	2.27	0.108	-.0879493	.5239173
x10	.0440871	.0898938	0.49	0.657	-.2419952	.3301694
x12	-.0160907	.0466282	-0.35	0.753	-.1644824	.132301
x18	.0083846	.0995324	0.08	0.938	-.3083719	.3251412
x19	.0213409	.0884904	0.24	0.825	-.260275	.3029567
x20	.0037407	.0423211	0.09	0.935	-.1309438	.1384252
y192	-1.571287	.4985057	-3.15	0.051	-3.157755	.0151809
y193	-.5457114	.1362654	-4.00	0.028	-.9793686	-.1120543
_cons	-.211145	.0606466	-3.48	0.040	-.4041497	-.0181403

```

. test y192 y193
( 1) y192 = 0
( 2) y193 = 0
      F( 2, 3) = 8.71
      Prob > F = 0.0563

```

. \*20 test all actual variables and diff. variables snow

. reg lnb x14 x21,robust cluster(PD)

Linear regression

Number of obs =	2048
F( 2, 3) =	40.63
Prob > F =	0.0067
R-squared =	0.1133
Root MSE =	.39989

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x14	2.41e-06	1.79e-06	1.35	0.270	-3.28e-06	8.10e-06
x21	.0000241	3.44e-06	7.00	0.006	.0000131	.000035
_cons	-.2768166	.0125432	-22.07	0.000	-.3167347	-.2368985

. predict u20,r

. predict y20hat,xb

. reg lnb x14 x21 l.u20,robust cluster(PD)

Linear regression

Number of obs =	2044
F( 2, 3) =	.
Prob > F =	.
R-squared =	0.1744
Root MSE =	.38633

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x14	2.49e-06	1.54e-06	1.62	0.203	-2.39e-06	7.38e-06
x21	.0000217	3.47e-06	6.24	0.008	.0000106	.0000327
u20	-.263631	.0142656	-18.48	0.000	-.3090305	-.2182315
_cons	-.2794965	.0131618	-21.24	0.000	-.3213832	-.2376097

. gen y202=y20hat\*y20hat

. gen y203=y202\*y20hat

. reg lnb x14 x21 y202 y203, robust cluster(PD)

Linear regression

Number of obs =	2048
F( 2, 3) =	.
Prob > F =	.
R-squared =	0.1263
Root MSE =	.39715

(Std. Err. adjusted for 4 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x14	7.27e-06	2.40e-06	3.04	0.056	-3.52e-07	.0000149
x21	8.77e-06	7.69e-07	11.41	0.001	6.33e-06	.0000112
y202	.0321644	1.113251	0.03	0.979	-3.510697	3.575026
y203	1.913976	1.562699	1.22	0.308	-3.059229	6.887181
_cons	-.2376768	.0367979	-6.46	0.008	-.3547841	-.1205696

. test y202 y203

( 1) y202 = 0

( 2) y203 = 0

F( 2, 3) =	14.77
Prob > F =	0.0280

## Month

```
. xtfisher lnb, lags(5)
```

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

```
chi2(12) = 521.0439
Prob > chi2 = 0.0000
```

```
. xtfisher x1, lags(5)
```

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

```
chi2(12) = 478.5539
Prob > chi2 = 0.0000
```

```
. xtfisher x2, lags(5)
```

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

```
chi2(12) = 481.8483
Prob > chi2 = 0.0000
```

```
. xtfisher x3, lags(5)
```

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

```
chi2(12) = 506.2766
Prob > chi2 = 0.0000
```

```
. xtfisher x4, lags(5)
```

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

```
chi2(12) = 506.0780
Prob > chi2 = 0.0000
```

```
. xtfisher x5, lags(5)
```

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

```
chi2(12) = 461.0476
Prob > chi2 = 0.0000
```

```
. xtfisher x6, lags(5)
```

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

```
chi2(12) = 459.5460
Prob > chi2 = 0.0000
```

. xtfisher x7, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(12) = 544.1961  
Prob > chi2 = 0.0000

. xtfisher x8, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(12) = 486.8758  
Prob > chi2 = 0.0000

. xtfisher x9, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(12) = 524.0383  
Prob > chi2 = 0.0000

. xtfisher x10, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(12) = 471.8921  
Prob > chi2 = 0.0000

. xtfisher x11, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(12) = 451.6180  
Prob > chi2 = 0.0000

. xtfisher x12, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(12) = 450.7177  
Prob > chi2 = 0.0000

. xtfisher x13, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(12) = 656.8093  
Prob > chi2 = 0.0000

. xtfisher x14, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(12) = **625.2351**  
Prob > chi2 = **0.0000**

. xtfisher x15, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(12) = **447.6786**  
Prob > chi2 = **0.0000**

. xtfisher x16, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(12) = **351.9869**  
Prob > chi2 = **0.0000**

. xtfisher x17, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(12) = **397.2518**  
Prob > chi2 = **0.0000**

. xtfisher x18, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(12) = **301.1371**  
Prob > chi2 = **0.0000**

. xtfisher x19, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(12) = **318.3473**  
Prob > chi2 = **0.0000**

. xtfisher x20, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(12) = **363.6403**  
Prob > chi2 = **0.0000**

. xtfisher x21, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(12) = **318.1910**  
Prob > chi2 = **0.0000**

. \*1 test actual variables

. reg lnb x2 x4 x6 x8 x10 x12 x14,robust cluster(PD)

Linear regression

Number of obs = 2262  
 F( 4, 5) = .  
 Prob > F = .  
 R-squared = 0.3691  
 Root MSE = .1637

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	.0013533	.0010258	1.32	0.244	-.0012836	.0039902
x4	.0027753	.000617	4.50	0.006	.0011893	.0043613
x6	-.005138	.000642	-8.00	0.000	-.0067884	-.0034876
x8	.0513436	.0030875	16.63	0.000	.043407	.0592803
x10	-.0083394	.0014014	-5.95	0.002	-.0119419	-.004737
x12	.008711	.0027877	3.12	0.026	.0015449	.0158771
x14	-7.59e-07	4.12e-07	-1.84	0.125	-1.82e-06	3.00e-07
_cons	-.0028314	.0128756	-0.22	0.835	-.0359291	.0302664

. test x2 x4 x6

( 1) x2 = 0  
 ( 2) x4 = 0  
 ( 3) x6 = 0

F( 3, 5) = 58.68  
 Prob > F = 0.0003

. test x8 x10 x12

( 1) x8 = 0  
 ( 2) x10 = 0  
 ( 3) x12 = 0

F( 3, 5) = 97.34  
 Prob > F = 0.0001

. predict u,r

. predict yhat,xb

. reg lnb x2 x4 x6 x8 x10 x12 x14 l.u,robust cluster(PD)

Linear regression

Number of obs = 2256  
 F( 4, 5) = .  
 Prob > F = .  
 R-squared = 0.3695  
 Root MSE = .16388

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	.0012964	.0010051	1.29	0.254	-.0012873	.0038801
x4	.0028183	.0006477	4.35	0.007	.0011532	.0044833
x6	-.0051333	.00064	-8.02	0.000	-.0067785	-.0034882
x8	.0518707	.0030583	16.96	0.000	.044009	.0597323
x10	-.0087439	.0016216	-5.39	0.003	-.0129123	-.0045755
x12	.008922	.0029408	3.03	0.029	.0013625	.0164815
x14	-7.84e-07	4.23e-07	-1.85	0.123	-1.87e-06	3.05e-07
u						
l1.	-.02998	.025657	-1.17	0.295	-.0959335	.0359734
_cons	-.002187	.0126577	-0.17	0.870	-.0347246	.0303506



```

. gen y2=yhat*yhat
.
. gen y3=y2*yhat
.
. reg lnb x2 x4 x6 x8 x10 x12 x14 y2 y3, robust cluster(PD)
Linear regression                               Number of obs = 2262
                                                F( 4, 5) = .
                                                Prob > F = .
                                                R-squared = 0.3944
                                                Root MSE = .16046
                                                (Std. Err. adjusted for 6 clusters in PD)

```

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	.002436	.0005938	4.10	0.009	.0009095	.0039625
x4	.0025123	.0005058	4.97	0.004	.0012122	.0038124
x6	-.0064944	.0006605	-9.83	0.000	-.0081922	-.0047966
x8	.0691744	.0058481	11.83	0.000	.0541413	.0842075
x10	-.013396	.0012325	-10.87	0.000	-.0165643	-.0102278
x12	.0111583	.0026898	4.15	0.009	.0042439	.0180727
x14	-6.98e-07	3.65e-07	-1.91	0.114	-1.64e-06	2.39e-07
y2	.0679128	.5996392	0.11	0.914	-1.473509	1.609334
y3	-1.905818	.6297979	-3.03	0.029	-3.524765	-.2868714
_cons	-.0096004	.0110232	-0.87	0.424	-.0379363	.0187356

```

. test y2 y3
( 1) y2 = 0
( 2) y3 = 0
      F( 2, 5) = 31.94
      Prob > F = 0.0014

```

. \*2 test actual variables reservoir level

. reg lnb x2 x4 x6,robust cluster(PD)

Linear regression Number of obs = 2262  
F( 3, 5) = 50.41  
Prob > F = 0.0004  
R-squared = 0.1576  
Root MSE = .189

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	<b>-.0047398</b>	<b>.0012529</b>	<b>-3.78</b>	<b>0.013</b>	<b>-.0079604</b>	<b>-.0015192</b>
x4	<b>.0074123</b>	<b>.0010018</b>	<b>7.40</b>	<b>0.001</b>	<b>.0048371</b>	<b>.0099876</b>
x6	<b>-.000924</b>	<b>.0012078</b>	<b>-0.76</b>	<b>0.479</b>	<b>-.0040289</b>	<b>.0021809</b>
_cons	<b>-.009591</b>	<b>.0190194</b>	<b>-0.50</b>	<b>0.635</b>	<b>-.0584819</b>	<b>.0392998</b>

. predict u2,r

. predict y2hat,xb

. reg lnb x2 x4 x6 l.u2,robust cluster(PD)

Linear regression Number of obs = 2256  
F( 4, 5) = 724.80  
Prob > F = 0.0000  
R-squared = 0.1761  
Root MSE = .18717

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	<b>-.0037814</b>	<b>.0009764</b>	<b>-3.87</b>	<b>0.012</b>	<b>-.0062915</b>	<b>-.0012714</b>
x4	<b>.0064399</b>	<b>.0008585</b>	<b>7.50</b>	<b>0.001</b>	<b>.0042331</b>	<b>.0086468</b>
x6	<b>-.0009869</b>	<b>.0011411</b>	<b>-0.86</b>	<b>0.427</b>	<b>-.0039203</b>	<b>.0019465</b>
u2						
L1.	<b>.1543036</b>	<b>.0358377</b>	<b>4.31</b>	<b>0.008</b>	<b>.06218</b>	<b>.2464273</b>
_cons	<b>-.0105085</b>	<b>.017545</b>	<b>-0.60</b>	<b>0.575</b>	<b>-.0556095</b>	<b>.0345924</b>

. gen y22=y2hat\*y2hat

. gen y23=y22\*y2hat

. reg lnb x2 x4 x6 y22 y23, robust cluster(PD)

Linear regression Number of obs = 2262  
F( 4, 5) = .  
Prob > F = .  
R-squared = 0.1847  
Root MSE = .18602

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	<b>-.0074547</b>	<b>.0010196</b>	<b>-7.31</b>	<b>0.001</b>	<b>-.0100756</b>	<b>-.0048337</b>
x4	<b>.0112436</b>	<b>.0017609</b>	<b>6.39</b>	<b>0.001</b>	<b>.0067171</b>	<b>.0157701</b>
x6	<b>-.0011829</b>	<b>.0011058</b>	<b>-1.07</b>	<b>0.334</b>	<b>-.0040254</b>	<b>.0016595</b>
y22	<b>.8680357</b>	<b>1.02887</b>	<b>0.84</b>	<b>0.437</b>	<b>-1.776758</b>	<b>3.512829</b>
y23	<b>-17.54398</b>	<b>4.191682</b>	<b>-4.19</b>	<b>0.009</b>	<b>-28.31904</b>	<b>-6.768918</b>
_cons	<b>-.0209394</b>	<b>.0193115</b>	<b>-1.08</b>	<b>0.328</b>	<b>-.070581</b>	<b>.0287023</b>

. test y22 y23

( 1) **y22 = 0**  
( 2) **y23 = 0**

F( 2, 5) = 21.82  
Prob > F = 0.0034

. \*3 test actual variables inflow

. reg lnb x8 x10 x12,robust cluster(PD)

Linear regression

Number of obs =	2262
F( 3, 5) =	59.15
Prob > F =	0.0003
R-squared =	0.2685
Root MSE =	.17612

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x8	.0503508	.0058288	8.64	0.000	.0353675	.065334
x10	-.0080418	.0040451	-1.99	0.104	-.0184401	.0023565
x12	-.0042305	.0021341	-1.98	0.104	-.0097164	.0012553
_cons	-.0401549	.0083485	-4.81	0.005	-.0616155	-.0186944

. predict u3, r

. predict y3hat,xb

. reg lnb x8 x10 x12 l.u3,robust cluster(PD)

Linear regression

Number of obs =	2256
F( 4, 5) =	249.00
Prob > F =	0.0000
R-squared =	0.2717
Root MSE =	.17598

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x8	.0492053	.0055838	8.81	0.000	.0348518	.0635589
x10	-.0070651	.0039562	-1.79	0.134	-.0172349	.0031048
x12	-.0043878	.0020445	-2.15	0.085	-.0096433	.0008678
u3						
l1.	.0675479	.0269607	2.51	0.054	-.0017568	.1368526
_cons	-.0398552	.0076491	-5.21	0.003	-.0595177	-.0201927

. gen y32=y3hat\*y3hat

. gen y33=y32\*y3hat

. reg lnb x8 x10 x12 y32 y33, robust cluster(PD)

Linear regression

Number of obs =	2262
F( 4, 5) =	.
Prob > F =	.
R-squared =	0.3027
Root MSE =	.17203

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x8	.0985048	.0103524	9.52	0.000	.071893	.1251166
x10	-.0159701	.0049763	-3.21	0.024	-.0287621	-.0031781
x12	-.0098171	.0015706	-6.25	0.002	-.0138543	-.0057798
y32	-4.548277	.6799567	-6.69	0.001	-6.296161	-2.800393
y33	3.970379	.7914003	5.02	0.004	1.936019	6.004738
_cons	-.0754034	.0125085	-6.03	0.002	-.1075575	-.0432494

. test y32 y33

( 1) y32 = 0  
( 2) y33 = 0

F( 2, 5) = 31.62  
Prob > F = 0.0015

. \*4 test actual variables snow

. reg lnb x14,robust cluster(PD)

Linear regression

Number of obs =	2262
F( 1, 5) =	2.54
Prob > F =	0.1720
R-squared =	0.0242
Root MSE =	.20332

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x14	-9.26e-07	5.81e-07	-1.59	0.172	-2.42e-06	5.68e-07
_cons	.0794559	.0214147	3.71	0.014	.0244077	.1345041

. predict u4,r

. predict y4hat,xb

. reg lnb x14 l.u4,robust cluster(PD)

Linear regression

Number of obs =	2256
F( 2, 5) =	69.39
Prob > F =	0.0002
R-squared =	0.0584
Root MSE =	.2

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x14	-5.52e-07	5.37e-07	-1.03	0.351	-1.93e-06	8.28e-07
u4	.1978945	.0234257	8.45	0.000	.1376769	.2581122
_cons	.0685471	.0192139	3.57	0.016	.0191563	.1179379

. gen y42=y4hat\*y4hat

. gen y43=y42\*y4hat

. reg lnb x14 y42 y43, robust cluster(PD)

Linear regression

Number of obs =	2262
F( 3, 5) =	110.35
Prob > F =	0.0001
R-squared =	0.1166
Root MSE =	.19354

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x14	2.16e-06	8.88e-07	2.43	0.059	-1.26e-07	4.44e-06
y42	35.42096	17.07137	2.07	0.093	-8.462403	79.30433
y43	220.5345	232.4352	0.95	0.386	-376.9593	818.0283
_cons	-.1997365	.0493448	-4.05	0.010	-.3265815	-.0728916

. test y42 y43

( 1) y42 = 0  
( 2) y43 = 0

F( 2, 5) =	22.07
Prob > F =	0.0033

. \*5 Test all seasonal variables

. reg lnb x1 x3 x5 x7 x9 x11 x13,robust cluster(PD)

Linear regression Number of obs = 2262  
F( 4, 5) = .  
Prob > F = .  
R-squared = 0.3290  
Root MSE = .16882

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	-.0209254	.0081725	-2.56	0.051	-.0419335	.0000826
x3	.0471239	.0114094	4.13	0.009	.0177952	.0764526
x5	-.0285405	.0034044	-8.38	0.000	-.0372917	-.0197894
x7	-.008234	.012821	-0.64	0.549	-.0411914	.0247233
x9	.0492429	.0160454	3.07	0.028	.007997	.0904888
x11	-.0042229	.0089047	-0.47	0.655	-.0271131	.0186674
x13	8.16e-06	1.98e-06	4.12	0.009	3.06e-06	.0000133
_cons	.0276461	.0144405	1.91	0.114	-.0094743	.0647665

. test x1 x3 x5

- ( 1) x1 = 0
- ( 2) x3 = 0
- ( 3) x5 = 0

F( 3, 5) = 74.99  
Prob > F = 0.0001

. test x7 x9 x11

- ( 1) x7 = 0
- ( 2) x9 = 0
- ( 3) x11 = 0

F( 3, 5) = 279.50  
Prob > F = 0.0000

. predict u5,r

. predict y5hat,xb

. reg lnb x1 x3 x5 x7 x9 x11 x13 l.u5,robust cluster(PD)

Linear regression Number of obs = 2256  
F( 4, 5) = .  
Prob > F = .  
R-squared = 0.3383  
Root MSE = .16789

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	-.0218854	.0075073	-2.92	0.033	-.0411834	-.0025874
x3	.0493996	.0103892	4.75	0.005	.0226934	.0761058
x5	-.0299453	.0033505	-8.94	0.000	-.0385581	-.0213325
x7	-.0106453	.0134217	-0.79	0.464	-.0451468	.0238563
x9	.0517465	.0160407	3.23	0.023	.0105127	.0929803
x11	-.0043911	.0086675	-0.51	0.634	-.0266717	.0178894
x13	8.60e-06	1.87e-06	4.61	0.006	3.81e-06	.0000134
u5						
l1.	-.1138092	.0197077	-5.77	0.002	-.1644695	-.0631489
_cons	.0279656	.0147437	1.90	0.116	-.0099345	.0658656

```

. gen y52=y5hat*y5hat
.
. gen y53=y52*y5hat
.
. reg lnb x1 x3 x5 x7 x9 x11 x13 y52 y53, robust cluster(PD)
Linear regression                               Number of obs =   2262
                                                F( 4,          5) =      .
                                                Prob > F       =      .
                                                R-squared     =   0.3462
                                                Root MSE     =   .16673

```

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	-.0423267	.0085679	-4.94	0.004	-.0643513	-.0203021
x3	.0865358	.0129449	6.68	0.001	.05326	.1198117
x5	-.0479357	.0051616	-9.29	0.000	-.061204	-.0346675
x7	.0014698	.0134062	0.11	0.917	-.032992	.0359315
x9	.0331978	.0191575	1.73	0.144	-.0160481	.0824437
x11	.0094395	.0091346	1.03	0.349	-.0140416	.0329207
x13	.0000159	2.22e-06	7.14	0.001	.0000101	.0000216
y52	2.82843	.788526	3.59	0.016	.8014592	4.8554
y53	-8.717011	2.651796	-3.29	0.022	-15.53367	-1.900351
_cons	.0334545	.0098544	3.39	0.019	.0081229	.0587861

```

. test y52 y53
( 1) y52 = 0
( 2) y53 = 0
      F( 2,          5) =   11.86
      Prob > F =   0.0126

```

. \*6 Test all seasonal variables reservoir level

. reg lnb x1 x3 x5,robust cluster(PD)

Linear regression

Number of obs =	2262
F( 3, 5) =	159.16
Prob > F =	0.0000
R-squared =	0.2161
Root MSE =	.18232

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	-.0148194	.0025945	-5.71	0.002	-.0214889	-.00815
x3	.0144633	.0036747	3.94	0.011	.0050172	.0239094
x5	.0021263	.0010725	1.98	0.104	-.0006305	.0048832
_cons	.0425453	.016232	2.62	0.047	.0008196	.084271

. predict u6,r

. predict y6hat,xb

. reg lnb x1 x3 x5 l.u6,robust cluster(PD)

Linear regression

Number of obs =	2256
F( 4, 5) =	200.46
Prob > F =	0.0000
R-squared =	0.2162
Root MSE =	.18256

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	-.0147356	.0026484	-5.56	0.003	-.0215436	-.0079277
x3	.0143684	.0037402	3.84	0.012	.0047538	.0239829
x5	.0021293	.0010437	2.04	0.097	-.0005535	.0048122
u6						
L1.	.0190384	.0321462	0.59	0.579	-.0635961	.1016729
_cons	.0424362	.0160166	2.65	0.045	.0012643	.0836082

. gen y62=y6hat\*y6hat

. gen y63=y62\*y6hat

. reg lnb x1 x3 x5 y62 y63, robust cluster(PD)

Linear regression

Number of obs =	2262
F( 4, 5) =	.
Prob > F =	.
R-squared =	0.2879
Root MSE =	.17385

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	-.0180267	.0026732	-6.74	0.001	-.0248983	-.0111551
x3	.0190728	.0026331	7.24	0.001	.0123043	.0258414
x5	.0004746	.0015194	0.31	0.767	-.0034311	.0043804
y62	6.495503	.9282611	7.00	0.001	4.109332	8.881674
y63	-20.88994	3.659535	-5.71	0.002	-30.29708	-11.48281
_cons	.036267	.0112011	3.24	0.023	.0074736	.0650603

. test y62 y63

( 1) y62 = 0

( 2) y63 = 0

F( 2, 5) =	29.27
Prob > F =	0.0017

. \*7 Test all seasonal variables inflow

. reg lnb x7 x9 x11,robust cluster(PD)

Linear regression

Number of obs =	2262
F( 3, 5) =	32.55
Prob > F =	0.0010
R-squared =	0.2086
Root MSE =	.18318

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x7	-.0090799	.0211761	-0.43	0.686	-.0635147	.0453548
x9	.0527473	.0205355	2.57	0.050	-.0000408	.1055354
x11	-.0294454	.0085283	-3.45	0.018	-.0513682	-.0075226
_cons	-.0083641	.0095648	-0.87	0.422	-.0329511	.0162229

. predict u7,r

. predict y7hat,xb

. reg lnb x7 x9 x11 l.u7,robust cluster(PD)

Linear regression

Number of obs =	2256
F( 4, 5) =	41.55
Prob > F =	0.0005
R-squared =	0.2091
Root MSE =	.18338

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x7	-.0099123	.0205212	-0.48	0.649	-.0626636	.042839
x9	.0534353	.0201922	2.65	0.046	.0015297	.1053409
x11	-.0295982	.0084909	-3.49	0.018	-.0514248	-.0077716
u7						
L1.	.0289866	.0390224	0.74	0.491	-.0713237	.1292968
_cons	-.008079	.0092061	-0.88	0.420	-.0317441	.015586

. gen y72=y7hat\*y7hat

. gen y73=y72\*y7hat

. reg lnb x7 x9 x11 y72 y73, robust cluster(PD)

Linear regression

Number of obs =	2262
F( 4, 5) =	.
Prob > F =	.
R-squared =	0.2950
Root MSE =	.17297

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x7	-.0365894	.0232891	-1.57	0.177	-.096456	.0232772
x9	.1823333	.0294014	6.20	0.002	.1067545	.2579121
x11	-.1024183	.0118965	-8.61	0.000	-.1329991	-.0718375
y72	-13.71666	2.640835	-5.19	0.003	-20.50514	-6.928177
y73	17.29183	4.942668	3.50	0.017	4.586297	29.99736
_cons	-.0386398	.0126393	-3.06	0.028	-.0711302	-.0061494

. test y72 y73

( 1) y72 = 0  
( 2) y73 = 0

F( 2, 5) =	37.44
Prob > F =	0.0010



. \*8 Test all seasonal variables snow

. reg lnb x13,robust cluster(PD)

Linear regression

Number of obs =	2262
F( 1, 5) =	4.64
Prob > F =	0.0837
R-squared =	0.0540
Root MSE =	.20019

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x13	<b>-1.48e-06</b>	<b>6.86e-07</b>	<b>-2.15</b>	<b>0.084</b>	<b>-3.24e-06</b>	<b>2.85e-07</b>
_cons	<b>.0950878</b>	<b>.0239938</b>	<b>3.96</b>	<b>0.011</b>	<b>.0334097</b>	<b>.1567659</b>

. predict u8,r

. predict y8hat,xb

. reg lnb x13 l.u8,robust cluster(PD)

Linear regression

Number of obs =	2256
F( 2, 5) =	120.65
Prob > F =	0.0001
R-squared =	0.0839
Root MSE =	.19728

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x13	<b>-1.19e-06</b>	<b>6.32e-07</b>	<b>-1.88</b>	<b>0.119</b>	<b>-2.82e-06</b>	<b>4.37e-07</b>
u8	<b>.1843256</b>	<b>.0226842</b>	<b>8.13</b>	<b>0.000</b>	<b>.1260139</b>	<b>.2426373</b>
_cons	<b>.0867874</b>	<b>.0216123</b>	<b>4.02</b>	<b>0.010</b>	<b>.0312312</b>	<b>.1423435</b>

. gen y82=y8hat\*y8hat

. gen y83=y82\*y8hat

. reg lnb x13 y82 y83, robust cluster(PD)

Linear regression

Number of obs =	2262
F( 3, 5) =	118.35
Prob > F =	0.0000
R-squared =	0.1346
Root MSE =	.19156

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x13	<b>5.26e-07</b>	<b>1.15e-06</b>	<b>0.46</b>	<b>0.666</b>	<b>-2.42e-06</b>	<b>3.48e-06</b>
y82	<b>24.86909</b>	<b>8.732913</b>	<b>2.85</b>	<b>0.036</b>	<b>2.42042</b>	<b>47.31776</b>
y83	<b>15.52356</b>	<b>119.4865</b>	<b>0.13</b>	<b>0.902</b>	<b>-291.6263</b>	<b>322.6734</b>
_cons	<b>-.0930379</b>	<b>.0543114</b>	<b>-1.71</b>	<b>0.147</b>	<b>-.2326498</b>	<b>.046574</b>

. test y82 y83

( 1) **y82 = 0**  
 ( 2) **y83 = 0**

F( 2, 5) =	<b>18.81</b>
Prob > F =	<b>0.0047</b>

. \*9 test all actual and season variables

. reg lnb x1 x2 x3 x4 x5 x6 x7 x8 x9 x10 x11 x12 x13 x14,robust cluster(PD)

Linear regression

Number of obs = 2262  
 F( 4, 5) = .  
 Prob > F = .  
 R-squared = 0.5619  
 Root MSE = .13663

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	-.0368756	.0078693	-4.69	0.005	-.0571044	-.0166469
x2	.0081106	.0006293	12.89	0.000	.006493	.0097283
x3	.0576028	.0106485	5.41	0.003	.0302299	.0849757
x4	.0032006	.0002656	12.05	0.000	.0025178	.0038834
x5	-.0305737	.0031185	-9.80	0.000	-.0385902	-.0225573
x6	-.003268	.0005827	-5.61	0.002	-.0047659	-.0017701
x7	-.0240236	.0121225	-1.98	0.104	-.0551853	.0071382
x8	.0158953	.0025549	6.22	0.002	.0093278	.0224628
x9	.0410233	.0128489	3.19	0.024	.0079942	.0740524
x10	.0028409	.0025828	1.10	0.321	-.0037983	.0094801
x11	-.0143238	.0084532	-1.69	0.151	-.0360534	.0074058
x12	.0072666	.0017356	4.19	0.009	.0028052	.011728
x13	.0000109	2.20e-07	4.97	0.004	5.28e-06	.0000166
x14	1.29e-07	4.72e-07	0.27	0.796	-1.09e-06	1.34e-06
_cons	.024453	.0116056	2.11	0.089	-.0053802	.0542862

. test x1 x2 x3 x4 x5 x6

( 1) x1 = 0  
 ( 2) x2 = 0  
 ( 3) x3 = 0  
 ( 4) x4 = 0  
 ( 5) x5 = 0  
 ( 6) x6 = 0  
 Constraint 4 dropped  
 F( 5, 5) = 77.90  
 Prob > F = 0.0001

. test x1 x3 x5

( 1) x1 = 0  
 ( 2) x3 = 0  
 ( 3) x5 = 0  
 F( 3, 5) = 73.36  
 Prob > F = 0.0001

. test x2 x3 x5

( 1) x2 = 0  
 ( 2) x3 = 0  
 ( 3) x5 = 0  
 F( 3, 5) = 88.55  
 Prob > F = 0.0001

. test x7 x8 x9 x10 x11 x12

( 1) x7 = 0  
 ( 2) x8 = 0  
 ( 3) x9 = 0  
 ( 4) x10 = 0  
 ( 5) x11 = 0  
 ( 6) x12 = 0  
 Constraint 2 dropped  
 F( 5, 5) = 43.31  
 Prob > F = 0.0004

. test x7 x9 x11

( 1) x7 = 0  
 ( 2) x9 = 0  
 ( 3) x11 = 0  
 F( 3, 5) = 10.08  
 Prob > F = 0.0146

. test x8 x10 x12

( 1) x8 = 0  
 ( 2) x10 = 0  
 ( 3) x12 = 0  
 F( 3, 5) = 14.97  
 Prob > F = 0.0062

. test x13 x14

( 1) x13 = 0  
 ( 2) x14 = 0  
 F( 2, 5) = 545.99  
 Prob > F = 0.0000

```

. predict u9,r
.
. predict y9hat,xb
.
. reg lnb x1 x2 x3 x4 x5 x6 x7 x8 x9 x10 x11 x12 x13 x14 l.u9,robust cluster(PD)

```

Linear regression

Number of obs =	2256
F( 4, 5) =	.
Prob > F =	.
R-squared =	<b>0.5645</b>
Root MSE =	<b>.13641</b>

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	-.036125	.0076274	-4.74	0.005	-.0557319	-.0165182
x2	.0077552	.0006466	11.99	0.000	.006093	.0094174
x3	.057216	.0100663	5.68	0.002	.0313398	.0830923
x4	.0031628	.0003015	10.49	0.000	.0023877	.0039379
x5	-.0309981	.0029064	-10.67	0.000	-.0384693	-.0235268
x6	-.0028309	.0005957	-4.75	0.005	-.0043622	-.0012997
x7	-.0269299	.012346	-2.18	0.081	-.0586662	.0048064
x8	.0178885	.0022089	8.10	0.000	.0122104	.0235665
x9	.0437989	.0131824	3.32	0.021	.0099124	.0776854
x10	.0017003	.0023036	0.74	0.494	-.0042211	.0076218
x11	-.0151976	.0086118	-1.76	0.138	-.0373349	.0069396
x12	.0074778	.0016978	4.40	0.007	.0031134	.0118421
x13	.0000109	2.11e-06	5.20	0.003	5.54e-06	.0000164
x14	7.61e-09	4.68e-07	0.02	0.988	-1.20e-06	1.21e-06
u9						
_l1.	-.083114	.0207746	-4.00	0.010	-.1365169	-.0297112
_cons	.0243212	.0115856	2.10	0.090	-.0054606	.0541031

```

. gen y92=y9hat*y9hat
.
. gen y93=y92*y9hat
.
. reg lnb x1 x2 x3 x4 x5 x6 x7 x8 x9 x10 x11 x12 x13 x14 y92 y93, robust cluster(> PD)

```

Linear regression

Number of obs =	2262
F( 4, 5) =	.
Prob > F =	.
R-squared =	<b>0.5775</b>
Root MSE =	<b>.13423</b>

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	-.0359913	.0052934	-6.80	0.001	-.0495984	-.0223842
x2	.005789	.0007315	7.91	0.001	.0039085	.0076694
x3	.058548	.0068073	8.60	0.000	.0410492	.0760468
x4	.0042952	.0003627	11.84	0.000	.003363	.0052274
x5	-.0324304	.0019382	-16.73	0.000	-.0374126	-.0274481
x6	-.0024684	.0004009	-6.16	0.002	-.0034989	-.0014379
x7	-.0089129	.0125521	-0.71	0.509	-.0411792	.0233535
x8	.0062313	.0017727	3.52	0.017	.0016745	.0107882
x9	.0282971	.0138343	2.05	0.096	-.0072651	.0638592
x10	.0030668	.0026677	1.15	0.302	-.0037906	.0099242
x11	-.0069592	.0091165	-0.76	0.480	-.0303939	.0164755
x12	.0069153	.0011823	5.85	0.002	.0038761	.0099545
x13	.0000111	1.46e-06	7.62	0.001	7.36e-06	.0000148
x14	2.77e-07	4.71e-07	0.59	0.582	-9.34e-07	1.49e-06
y92	.7837187	.0715947	10.95	0.000	.5996786	.9677588
y93	.1455143	.4160646	0.35	0.741	-.9240138	1.215043
_cons	.0343247	.0101374	3.39	0.020	.0082655	.0603838

```

. test y92 y93
( 1) y92 = 0
( 2) y93 = 0

F( 2, 5) = 102.34
Prob > F = 0.0001

```

. \*10 test all actual and season variables reservoir level

. reg lnb x1 x2 x3 x4 x5 x6,robust cluster(PD)

Linear regression

Number of obs = 2262  
 F( 4, 5) = .  
 Prob > F = .  
 R-squared = 0.4294  
 Root MSE = .15565

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	-.0194841	.0042141	-4.62	0.006	-.0303167	-.0086515
x2	.0068508	.0012683	5.40	0.003	.0035904	.0101112
x3	.0088224	.0045994	1.92	0.113	-.0030006	.0206455
x4	.0050021	.0008602	5.81	0.002	.0027908	.0072133
x5	.002321	.0007765	2.99	0.030	.0003249	.0043171
x6	-.0015401	.0007376	-2.09	0.091	-.0034362	.0003561
_cons	.0386153	.0150076	2.57	0.050	.000037	.0771936

. test x1 x3 x5

- ( 1) x1 = 0
- ( 2) x3 = 0
- ( 3) x5 = 0

F( 3, 5) = 96.06  
 Prob > F = 0.0001

. test x2 x4 x6

- ( 1) x2 = 0
- ( 2) x4 = 0
- ( 3) x6 = 0

F( 3, 5) = 232.12  
 Prob > F = 0.0000

. predict u10,r

. predict y10hat,xb

. reg lnb x1 x2 x3 x4 x5 x6 l.u10,robust cluster(PD)

Linear regression

Number of obs = 2256  
 F( 4, 5) = .  
 Prob > F = .  
 R-squared = 0.4360  
 Root MSE = .15496

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	-.0192751	.0042267	-4.56	0.006	-.0301401	-.0084101
x2	.0073109	.0012901	5.67	0.002	.0039944	.0106273
x3	.0079637	.0044218	1.80	0.132	-.003403	.0193304
x4	.005067	.0008717	5.81	0.002	.0028262	.0073079
x5	.0030099	.00083	3.63	0.015	.0008763	.0051435
x6	-.0021682	.0007213	-3.01	0.030	-.0040224	-.000314
u10						
l1.	.1102901	.0461511	2.39	0.062	-.0083451	.2289254
_cons	.0384646	.014688	2.62	0.047	.0007079	.0762212

```

. gen y102=y10hat*y10hat
.
. gen y103=y102*y10hat
.
. reg lnb x1 x2 x3 x4 x5 x6 y102 y103, robust cluster(PD)
Linear regression                               Number of obs =    2262
                                                F( 4,      5) =      .
                                                Prob > F      =      .
                                                R-squared    =    0.4810
                                                Root MSE    =    .14851

```

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	-.0133715	.0034632	-3.86	0.012	-.022274	-.0044691
x2	.0023441	.0009039	2.59	0.049	.0000205	.0046678
x3	.0075999	.0039732	1.91	0.114	-.0026135	.0178133
x4	.005411	.0010192	5.31	0.003	.002791	.008031
x5	-.0013385	.0011552	-1.16	0.299	-.0043081	.0016311
x6	.0002262	.0005572	0.41	0.702	-.0012061	.0016585
y102	1.636946	.1870845	8.75	0.000	1.15603	2.117862
y103	1.303025	.5259978	2.48	0.056	-.0490952	2.655146
_cons	.0496367	.0129247	3.84	0.012	.0164126	.0828608

```

. test y102 y103
( 1) y102 = 0
( 2) y103 = 0
      F( 2,      5) =    38.61
      Prob > F    =    0.0009

```

. \*11 test all actual and season variables inflow

. reg ln b x7 x8 x9 x10 x11 x12,robust cluster(PD)

Linear regression

Number of obs =	2262
F( 4, 5) =	.
Prob > F =	.
R-squared =	0.3148
Root MSE =	.17056

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x7	-.0584184	.0203096	-2.88	0.035	-.1106259	-.006211
x8	.0480135	.0054098	8.88	0.000	.0341072	.0619198
x9	.0660477	.0195061	3.39	0.020	.0159056	.1161898
x10	-.0058914	.0033185	-1.78	0.136	-.0144218	.002639
x11	-.0486493	.0091649	-5.31	0.003	-.0722085	-.0250901
x12	.0109023	.0024907	4.38	0.007	.0044997	.0173049
_cons	-.006816	.0096334	-0.71	0.511	-.0315795	.0179476

. test x7 x9 x11

- ( 1) x7 = 0
- ( 2) x9 = 0
- ( 3) x11 = 0

F( 3, 5) = 10.90  
 Prob > F = 0.0124

. test x8 x10 x12

- ( 1) x8 = 0
- ( 2) x10 = 0
- ( 3) x12 = 0

F( 3, 5) = 92.28  
 Prob > F = 0.0001

. predict u11,r

. predict y11hat,xb

. reg ln b x7 x8 x9 x10 x11 x12 l.u11,robust cluster(PD)

Linear regression

Number of obs =	2256
F( 4, 5) =	.
Prob > F =	.
R-squared =	0.3150
Root MSE =	.17078

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x7	-.0587746	.0200616	-2.93	0.033	-.1103446	-.0072046
x8	.0477728	.0052025	9.18	0.000	.0343994	.0611462
x9	.0663432	.0193306	3.43	0.019	.0166523	.1160341
x10	-.0056374	.0031383	-1.80	0.132	-.0137047	.0024299
x11	-.048643	.009077	-5.36	0.003	-.0719762	-.0253099
x12	.0107736	.0023768	4.53	0.006	.0046638	.0168834
u11						
l1.	.0207626	.0326133	0.64	0.552	-.0630725	.1045977
_cons	-.0067549	.0093449	-0.72	0.502	-.0307768	.0172669

```

. gen y112=y11hat*y11hat
.
. gen y113=y112*y11hat
.
. reg lnb x7 x8 x9 x10 x11 x12 y112 y113, robust cluster(PD)
Linear regression                               Number of obs =    2262
                                                F( 4,          5) =    .
                                                Prob > F       =    .
                                                R-squared     =    0.3587
                                                Root MSE     =    .16508

```

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x7	-.0891009	.0200077	-4.45	0.007	-.1405323	-.0376694
x8	.0861669	.0072661	11.86	0.000	.067489	.1048449
x9	.1018128	.0193191	5.27	0.003	.0521515	.1514741
x10	-.0107501	.0038048	-2.83	0.037	-.0205306	-.0009696
x11	-.0740387	.0086312	-8.58	0.000	-.0962258	-.0518516
x12	.0157833	.0023682	6.66	0.001	.0096956	.021871
y112	-3.71895	.5068204	-7.34	0.001	-5.021773	-2.416127
y113	2.937665	.7332999	4.01	0.010	1.052658	4.822673
_cons	-.0237019	.0100877	-2.35	0.066	-.0496331	.0022292

```

. test y112 y113
( 1) y112 = 0
( 2) y113 = 0
      F( 2,          5) =    149.38
      Prob > F       =    0.0000

```

. \*12 test all actual and season variables snow

. reg lnb x13 x14,robust cluster(PD)

Linear regression

Number of obs =	2262
F( 2, 5) =	15.97
Prob > F =	0.0067
R-squared =	0.0858
Root MSE =	.19684

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x13	-4.54e-06	1.02e-06	-4.44	0.007	-7.16e-06	-1.91e-06
x14	3.05e-06	5.40e-07	5.65	0.002	1.66e-06	4.44e-06
_cons	.0936507	.0241033	3.89	0.012	.0316911	.1556102

. predict u12,r

. predict y12hat,xb

. reg lnb x13 x14 l.u12,robust cluster(PD)

Linear regression

Number of obs =	2256
F( 3, 5) =	50.76
Prob > F =	0.0004
R-squared =	0.1365
Root MSE =	.19157

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x13	-4.81e-06	8.72e-07	-5.52	0.003	-7.05e-06	-2.57e-06
x14	3.72e-06	5.24e-07	7.09	0.001	2.37e-06	5.06e-06
u12	.2482193	.0340531	7.29	0.001	.1606831	.3357555
_cons	.0818197	.0214268	3.82	0.012	.0267404	.136899

. gen y122=y12hat\*y12hat

. gen y123=y122\*y12hat

. reg lnb x13 x14 y122 y123, robust cluster(PD)

Linear regression

Number of obs =	2262
F( 4, 5) =	2588.05
Prob > F =	0.0000
R-squared =	0.1158
Root MSE =	.19367

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x13	-4.24e-06	1.23e-06	-3.46	0.018	-7.40e-06	-1.09e-06
x14	2.93e-06	8.64e-07	3.40	0.019	7.12e-07	5.15e-06
y122	7.207397	1.933699	3.73	0.014	2.236666	12.17813
y123	1.050465	12.63953	0.08	0.937	-31.44049	33.54142
_cons	.0425985	.0225888	1.89	0.118	-.0154679	.100665

. test y122 y123

( 1) y122 = 0

( 2) y123 = 0

F( 2, 5) =	18.66
Prob > F =	0.0048



. \*13 Test all diff. variables

. reg lnb x15 x16 x17 x18 x19 x20 x21,robust cluster(PD)

Linear regression

Number of obs =	2262
F( 4, 5) =	.
Prob > F =	.
R-squared =	0.2564
Root MSE =	.17773

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x15	.0061869	.0005925	10.44	0.000	.0046638	.00771
x16	.006426	.0006193	10.38	0.000	.0048341	.0080178
x17	-.0053529	.0015443	-3.47	0.018	-.0093226	-.0013832
x18	.0288528	.0066059	4.37	0.007	.0118719	.0458338
x19	-.0202708	.0068808	-2.95	0.032	-.0379585	-.0025831
x20	.0169038	.0055164	3.06	0.028	.0027235	.031084
x21	2.81e-07	5.59e-07	0.50	0.637	-1.16e-06	1.72e-06
_cons	.0587331	.0088749	6.62	0.001	.0359194	.0815467

. test x15 x16 x17

- ( 1) x15 = 0
- ( 2) x16 = 0
- ( 3) x17 = 0

F( 3, 5) = 431.29  
Prob > F = 0.0000

. test x18 x19 x20

- ( 1) x18 = 0
- ( 2) x19 = 0
- ( 3) x20 = 0

F( 3, 5) = 9.17  
Prob > F = 0.0178

. predict u13,r

. predict y13hat,xb

. reg lnb x15 x16 x17 x18 x19 x20 x21 l.u13,robust cluster(PD)

Linear regression

Number of obs =	2256
F( 4, 5) =	.
Prob > F =	.
R-squared =	0.3462
Root MSE =	.16688

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x15	.0079998	.0011324	7.06	0.001	.0050889	.0109107
x16	.0054577	.000882	6.19	0.002	.0031905	.0077249
x17	-.0057545	.0015427	-3.73	0.014	-.00972	-.0017889
x18	.0170526	.0049126	3.47	0.018	.0044244	.0296808
x19	-.0099669	.0058816	-1.69	0.151	-.025086	.0051522
x20	.0117113	.0041424	2.83	0.037	.0010629	.0223597
x21	9.29e-07	5.81e-07	1.60	0.171	-5.65e-07	2.42e-06
u13						
l1.	.3582501	.0528368	6.78	0.001	.2224287	.4940715
_cons	.0636966	.005931	10.74	0.000	.0484505	.0789427

```

. gen y132=y13hat*y13hat
.
. gen y133=y132*y13hat
.
. reg lnb x15 x16 x17 x18 x19 x20 x21 y132 y133, robust cluster(PD)
Linear regression                               Number of obs =    2262
                                                F( 4,          5) =      .
                                                Prob > F       =
                                                R-squared     =    0.2842
                                                Root MSE     =    .17444
                                                (Std. Err. adjusted for 6 clusters in PD)

```

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x15	.0050356	.000397	12.69	0.000	.0040152	.006056
x16	.0048207	.0009845	4.90	0.004	.0022899	.0073514
x17	-.0036877	.0009212	-4.00	0.010	-.0060558	-.0013197
x18	.0063472	.00502	1.26	0.262	-.0065571	.0192515
x19	-.0077439	.0033862	-2.29	0.071	-.0164484	.0009605
x20	.010282	.0034002	3.02	0.029	.0015415	.0190225
x21	4.32e-07	5.30e-07	0.81	0.452	-9.31e-07	1.79e-06
y132	1.573538	1.244716	1.26	0.262	-1.626108	4.773183
y133	2.182655	2.736855	0.80	0.461	-4.852655	9.217965
_cons	.0342995	.0095525	3.59	0.016	.009744	.058855

```

. test y132 y133
( 1) y132 = 0
( 2) y133 = 0
      F( 2,          5) =    3.93
      Prob > F =    0.0941

```

. \*14 Test diff. variables reservoir level

. reg lnb x15 x16 x17,robust cluster(PD)

Linear regression Number of obs = 2262  
F( 3, 5) = 325.73  
Prob > F = 0.0000  
R-squared = 0.2228  
Root MSE = .18154

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x15	.007834	.0011161	7.02	0.001	.0049648	.0107031
x16	.0054073	.0011001	4.92	0.004	.0025793	.0082352
x17	-.0040834	.0010718	-3.81	0.013	-.0068386	-.0013282
_cons	.0688129	.011047	6.23	0.002	.0404156	.0972101

. predict u14,r

. predict y14hat,xb

. reg lnb x15 x16 x17 l.u14,robust cluster(PD)

Linear regression Number of obs = 2256  
F( 4, 5) = 303.42  
Prob > F = 0.0000  
R-squared = 0.3355  
Root MSE = .16809

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x15	.0091289	.0016732	5.46	0.003	.0048278	.01343
x16	.0053297	.0012455	4.28	0.008	.0021282	.0085313
x17	-.004737	.0012274	-3.86	0.012	-.0078922	-.0015819
u14						
L1.	.3808779	.0555846	6.85	0.001	.2379931	.5237627
_cons	.0711698	.0075578	9.42	0.000	.051742	.0905977

. gen y142=y14hat\*y14hat

. gen y143=y142\*y14hat

. reg lnb x15 x16 x17 y142 y143, robust cluster(PD)

Linear regression Number of obs = 2262  
F( 4, 5) = .  
Prob > F = .  
R-squared = 0.2788  
Root MSE = .17495

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x15	.0028745	.0006377	4.51	0.006	.0012351	.0045139
x16	.0020978	.0019303	1.09	0.327	-.0028643	.0070599
x17	-.0012893	.0004666	-2.76	0.040	-.0024888	-.0000898
y142	.8859508	1.115848	0.79	0.463	-1.982427	3.754328
y143	16.40475	3.996302	4.10	0.009	6.131924	26.67757
_cons	.0248239	.0120755	2.06	0.095	-.0062171	.055865

. test y142 y143

( 1) y142 = 0  
( 2) y143 = 0

F( 2, 5) = 8.43  
Prob > F = 0.0250

. \*15 Test diff. variables inflow

. reg lnb x18 x19 x20,robust cluster(PD)

Linear regression Number of obs = 2262  
F( 3, 5) = 104.23  
Prob > F = 0.0001  
R-squared = 0.0966  
Root MSE = .19572

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x18	.0562758	.0058264	9.66	0.000	.0412985	.0712531
x19	-.0267111	.0057038	-4.68	0.005	-.0413731	-.0120491
x20	.0156758	.0036186	4.33	0.007	.0063738	.0249778
_cons	.0424452	.0098806	4.30	0.008	.0170463	.0678441

. predict u15,r

. predict y15hat,xb

. reg lnb x18 x19 x20 l.u15,robust cluster(PD)

Linear regression Number of obs = 2256  
F( 4, 5) = 103.27  
Prob > F = 0.0001  
R-squared = 0.1478  
Root MSE = .19036

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x18	.0523595	.0055205	9.48	0.000	.0381687	.0665503
x19	-.0212231	.0053866	-3.94	0.011	-.0350699	-.0073764
x20	.0131518	.0029979	4.39	0.007	.0054454	.0208582
u15						
l1.	.242074	.0261425	9.26	0.000	.1748727	.3092754
_cons	.0440325	.007509	5.86	0.002	.0247301	.0633349

. gen y152=y15hat\*y15hat

. gen y153=y152\*y15hat

. reg lnb x15 x16 x17 y152 y153, robust cluster(PD)

Linear regression Number of obs = 2262  
F( 4, 5) = .  
Prob > F = .  
R-squared = 0.2920  
Root MSE = .17334

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x15	.0067461	.0005995	11.25	0.000	.0052051	.0082872
x16	.0054744	.0006632	8.25	0.000	.0037697	.0071792
x17	-.0045938	.0010559	-4.35	0.007	-.007308	-.0018797
y152	8.09797	1.695255	4.78	0.005	3.740178	12.45576
y153	-15.93024	3.233981	-4.93	0.004	-24.24345	-7.617023
_cons	.0306315	.0069674	4.40	0.007	.0127211	.0485418

. test y152 y153

( 1) y152 = 0

( 2) y153 = 0

F( 2, 5) = 12.13  
Prob > F = 0.0121

. \*16 Test diff. variables snow

. reg lnb x21,robust cluster(PD)

Linear regression

Number of obs = 2262  
 F( 1, 5) = 34.87  
 Prob > F = 0.0020  
 R-squared = 0.0311  
 Root MSE = .2026

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x21	3.01e-06	5.11e-07	5.90	0.002	1.70e-06	4.33e-06
_cons	.0501675	.0107498	4.67	0.005	.0225342	.0778007

. predict u16,r

. predict y16hat,xb

. reg lnb x21 l.u16,robust cluster(PD)

Linear regression

Number of obs = 2256  
 F( 2, 5) = 43.42  
 Prob > F = 0.0007  
 R-squared = 0.1140  
 Root MSE = .19401

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x21	3.77e-06	5.11e-07	7.38	0.001	2.46e-06	5.09e-06
u16	.2964547	.0321292	9.23	0.000	.2138638	.3790455
_cons	.0499347	.0076053	6.57	0.001	.0303845	.0694848

. gen y162=y16hat\*y16hat

. gen y163=y162\*y16hat

. reg lnb x21 y162 y163, robust cluster(PD)

Linear regression

Number of obs = 2262  
 F( 3, 5) = 12.51  
 Prob > F = 0.0092  
 R-squared = 0.0431  
 Root MSE = .20143

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x21	6.63e-06	2.64e-06	2.51	0.054	-1.62e-07	.0000134
y162	-19.3904	12.19646	-1.59	0.173	-50.74239	11.96158
y163	62.75112	36.60006	1.71	0.147	-31.33233	156.8346
_cons	.1022732	.0356492	2.87	0.035	.010634	.1939124

. test y162 y163

( 1) y162 = 0

( 2) y163 = 0

F( 2, 5) = 2.07  
 Prob > F = 0.2208

. \*17 test all actual variables and diff. variables

. reg lnb x2 x4 x6 x8 x10 x12 x14 x15 x16 x17 x18 x19 x20 x21,robust cluster(PD)

Linear regression

Number of obs = 2262  
 F( 4, 5) = .  
 Prob > F = .  
 R-squared = 0.5619  
 Root MSE = 0.13663

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	-.0287652	.0074177	-3.88	0.012	-.0478331	-.0096972
x4	.0608036	.0107738	5.64	0.002	.0331086	.0884986
x6	-.0338418	.0032901	-10.29	0.000	-.0422992	-.0253844
x8	-.0081281	.0105171	-0.77	0.475	-.0351632	.018907
x10	.043864	.014863	2.95	0.032	.0056573	.0820706
x12	-.0070571	.00933	-0.76	0.484	-.0310405	.0169264
x14	.0000111	1.74e-06	6.37	0.001	6.60e-06	.0000155
x15	.0368758	.0078693	4.69	0.005	.0166471	.0571044
x16	-.057603	.0106485	-5.41	0.003	-.0849758	-.0302302
x17	.0305738	.0031185	9.80	0.000	.0225574	.0385902
x18	.0240234	.0121225	1.98	0.104	-.0071384	.0551852
x19	-.041023	.0128489	-3.19	0.024	-.0740521	-.0079939
x20	.0143237	.0084532	1.69	0.151	-.007406	.0360533
x21	-.0000109	2.20e-06	-4.97	0.004	-.0000166	-5.28e-06
_cons	.024453	.0116056	2.11	0.089	-.0053802	.0542862

. test x2 x4 x6 x15 x16 x17

( 1) x2 = 0  
 ( 2) x4 = 0  
 ( 3) x6 = 0  
 ( 4) x15 = 0  
 ( 5) x16 = 0  
 ( 6) x17 = 0  
 Constraint 5 dropped  
 F( 5, 5) = 100.06  
 Prob > F = 0.0001

. test x2 x4 x6

( 1) x2 = 0  
 ( 2) x4 = 0  
 ( 3) x6 = 0  
 F( 3, 5) = 100.30  
 Prob > F = 0.0001

. test x15 x16 x17

( 1) x15 = 0  
 ( 2) x16 = 0  
 ( 3) x17 = 0  
 F( 3, 5) = 73.36  
 Prob > F = 0.0001

. test x8 x10 x12 x18 x19 x20

( 1) x8 = 0  
 ( 2) x10 = 0  
 ( 3) x12 = 0  
 ( 4) x18 = 0  
 ( 5) x19 = 0  
 ( 6) x20 = 0  
 Constraint 1 dropped  
 F( 5, 5) = 43.31  
 Prob > F = 0.0004

. test x8 x10 x12

( 1) x8 = 0  
 ( 2) x10 = 0  
 ( 3) x12 = 0  
 F( 3, 5) = 38.93  
 Prob > F = 0.0007

. test x18 x19 x20

( 1) x18 = 0  
 ( 2) x19 = 0  
 ( 3) x20 = 0  
 F( 3, 5) = 10.08  
 Prob > F = 0.0146

. test x14 x21

( 1) x14 = 0  
 ( 2) x21 = 0  
 F( 2, 5) = 546.01  
 Prob > F = 0.0000

```

. predict u17,r
.
. predict y17hat,xb
.
. reg lnb x2 x4 x6 x8 x10 x12 x14 x15 x16 x17 x18 x19 x20 x21 l.u17,robust cluste
> r(PD)

```

```

Linear regression                               Number of obs =    2256
                                                F( 4, 5) = .
                                                Prob > F = .
                                                R-squared =    0.5645
                                                Root MSE =    .13641

```

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	-.02837	.0071192	-3.98	0.010	-.0466705	-.0100694
x4	.060379	.010231	5.90	0.002	.0340794	.0866787
x6	-.0338291	.0030994	-10.91	0.000	-.0417963	-.0258619
x8	-.0090413	.0108592	-0.83	0.443	-.0369559	.0188732
x10	.045499	.0151462	3.00	0.030	.0065644	.0844336
x12	-.0077197	.0094257	-0.82	0.450	-.0319494	.0165099
x14	.000011	1.65e-06	6.64	0.001	6.72e-06	.0000152
x15	.0361252	.0076274	4.74	0.005	.0165184	.055732
x16	-.0572163	.0100662	-5.68	0.002	-.0830924	-.0313401
x17	.0309982	.0029064	10.67	0.000	.023527	.0384693
x18	.0269298	.012346	2.18	0.081	-.0048065	.058666
x19	-.0437986	.0131824	-3.32	0.021	-.0776851	-.0099122
x20	.0151975	.0086118	1.76	0.138	-.0069397	.0373347
x21	-.0000109	2.11e-06	-5.20	0.003	-.0000164	-5.54e-06
u17						
l1.	-.0831141	.0207746	-4.00	0.010	-.1365169	-.0297113
_cons	.0243212	.0115856	2.10	0.090	-.0054606	.0541031

```

. gen y172=y17hat*y17hat
.
. gen y173=y172*y17hat
.
. reg lnb x2 x4 x6 x8 x10 x12 x14 x15 x16 x17 x18 x19 x20 x21 y172 y173, robust c
> luster(PD)

```

```

Linear regression                               Number of obs =    2262
                                                F( 4, 5) = .
                                                Prob > F = .
                                                R-squared =    0.5775
                                                Root MSE =    .13423

```

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	-.0302024	.0055724	-5.42	0.003	-.0445266	-.0158782
x4	.0628433	.0069766	9.01	0.000	.0449094	.0807773
x6	-.0348988	.001729	-20.18	0.000	-.0393434	-.0304543
x8	-.0026814	.0112416	-0.24	0.821	-.0315787	.026216
x10	.0313636	.0159826	1.96	0.107	-.0097209	.0724482
x12	-.0000438	.0097291	-0.00	0.997	-.0250532	.0249656
x14	.0000114	1.03e-06	11.05	0.000	8.73e-06	.000014
x15	.0359914	.0052934	6.80	0.001	.0223843	.0495984
x16	-.0585481	.0068073	-8.60	0.000	-.0760468	-.0410495
x17	.0324304	.0019382	16.73	0.000	.0274482	.0374126
x18	.0089127	.0125522	0.71	0.509	-.0233537	.041179
x19	-.0282968	.0138343	-2.05	0.096	-.0638589	.0072652
x20	.0069591	.0091165	0.76	0.480	-.0164755	.0303937
x21	-.0000111	1.46e-06	-7.62	0.001	-.0000148	-7.36e-06
y172	.7837187	.0715942	10.95	0.000	.5996799	.9677576
y173	.1455167	.4160639	0.35	0.741	-.9240096	1.215043
_cons	.0343246	.0101375	3.39	0.020	.0082655	.0603838

```

. test y172 y173
( 1) y172 = 0
( 2) y173 = 0

F( 2, 5) = 102.34
Prob > F = 0.0001

```

. \*18 test all actual variables and diff. variables reservoir level

. reg lnb x2 x4 x6 x15 x16 x17,robust cluster(PD)

Linear regression Number of obs = 2262  
F( 4, 5) = .  
Prob > F = .  
R-squared = 0.4294  
Root MSE = .15565

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	-.0126333	.0032815	-3.85	0.012	-.0210686	-.0041979
x4	.0138245	.0039897	3.47	0.018	.0035686	.0240803
x6	.0007809	.0007918	0.99	0.369	-.0012544	.0028162
x15	.0194841	.0042141	4.62	0.006	.0086515	.0303167
x16	-.0088224	.0045994	-1.92	0.113	-.0206455	.0030006
x17	-.002321	.0007765	-2.99	0.030	-.0043171	-.0003249
_cons	.0386153	.0150076	2.57	0.050	.000037	.0771936

. test x2 x4 x6

- ( 1) x2 = 0
- ( 2) x4 = 0
- ( 3) x6 = 0

F( 3, 5) = 50.34  
Prob > F = 0.0004

. test x15 x16 x17

- ( 1) x15 = 0
- ( 2) x16 = 0
- ( 3) x17 = 0

F( 3, 5) = 96.06  
Prob > F = 0.0001

. predict u18,r

. predict y18hat,xb

. reg lnb x2 x4 x6 x15 x16 x17 l.u18,robust cluster(PD)

Linear regression Number of obs = 2256  
F( 4, 5) = .  
Prob > F = .  
R-squared = 0.4360  
Root MSE = .15496

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	-.0119642	.0032104	-3.73	0.014	-.0202167	-.0037117
x4	.0130307	.0038042	3.43	0.019	.0032518	.0228097
x6	.0008417	.0006741	1.25	0.267	-.0008911	.0025746
x15	.0192751	.0042267	4.56	0.006	.0084101	.0301401
x16	-.0079637	.0044218	-1.80	0.132	-.0193304	.003403
x17	-.0030099	.00083	-3.63	0.015	-.0051435	-.0008763
u18						
l1.	.1102901	.0461511	2.39	0.062	-.0083452	.2289254
_cons	.0384646	.014688	2.62	0.047	.0007079	.0762212



```

. gen y182=y18hat*y18hat
.
. gen y183=y182*y18hat
.
. reg lnb x2 x4 x6 x15 x16 x17 y182 y183, robust cluster(PD)
Linear regression                               Number of obs =    2262
                                                F( 4,          5) =      .
                                                Prob > F       =      .
                                                R-squared     =    0.4810
                                                Root MSE     =    .14851

```

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	-.0110274	.0028761	-3.83	0.012	-.0184205	-.0036343
x4	.0130109	.0032467	4.01	0.010	.0046651	.0213568
x6	-.0011123	.0010493	-1.06	0.338	-.0038095	.0015849
x15	.0133715	.0034632	3.86	0.012	.0044691	.022274
x16	-.0075999	.0039732	-1.91	0.114	-.0178133	.0026135
x17	.0013385	.0011552	1.16	0.299	-.0016311	.0043081
y182	1.636946	.1870844	8.75	0.000	1.156031	2.117862
y183	1.303026	.5259977	2.48	0.056	-.0490945	2.655146
_cons	.0496367	.0129247	3.84	0.012	.0164126	.0828608

```

. test y182 y183
( 1) y182 = 0
( 2) y183 = 0
      F( 2,          5) =    38.61
      Prob > F =    0.0009

```

. \*19 test all actual variables and diff. variables inflow

. reg lnb x8 x10 x12 x18 x19 x20,robust cluster(PD)

Linear regression Number of obs = 2262  
F( 4, 5) = .  
Prob > F = .  
R-squared = 0.3148  
Root MSE = .17056

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x8	-.010405	.0212498	-0.49	0.645	-.0650294	.0442195
x10	.0601563	.0210209	2.86	0.035	.0061204	.1141922
x12	-.037747	.0087171	-4.33	0.007	-.0601551	-.0153389
x18	.0584184	.0203096	2.88	0.035	.006211	.1106259
x19	-.0660477	.0195061	-3.39	0.020	-.1161898	-.0159056
x20	.0486493	.0091649	5.31	0.003	.0250901	.0722086
_cons	-.006816	.0096334	-0.71	0.511	-.0315795	.0179476

. test x8 x10 x12

- ( 1) x8 = 0
- ( 2) x10 = 0
- ( 3) x12 = 0

F( 3, 5) = 30.20  
Prob > F = 0.0013

. test x18 x19 x20

- ( 1) x18 = 0
- ( 2) x19 = 0
- ( 3) x20 = 0

F( 3, 5) = 10.90  
Prob > F = 0.0124

. predict u19,r

. predict y19hat,xb

. reg lnb x8 x10 x12 x18 x19 x20 l.u19,robust cluster(PD)

Linear regression Number of obs = 2256  
F( 4, 5) = .  
Prob > F = .  
R-squared = 0.3150  
Root MSE = .17078

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x8	-.0110018	.0207913	-0.53	0.619	-.0644476	.0424439
x10	.0607058	.0207478	2.93	0.033	.0073719	.1140397
x12	-.0378694	.0086605	-4.37	0.007	-.060132	-.0156069
x18	.0587746	.0200616	2.93	0.033	.0072046	.1103447
x19	-.0663432	.0193306	-3.43	0.019	-.1160341	-.0166523
x20	.048643	.009077	5.36	0.003	.0253098	.0719762
u19						
l1.	.0207626	.0326133	0.64	0.552	-.0630725	.1045977
_cons	-.0067549	.0093449	-0.72	0.502	-.0307768	.0172669

```

. gen y192=y19hat*y19hat
. gen y193=y192*y19hat
. reg lnb x8 x10 x12 x18 x19 x20 y192 y193, robust cluster(PD)
Linear regression                               Number of obs =    2262
                                                F( 4, 2257) =      .
                                                Prob > F      =    0.3587
                                                R-squared     =
                                                Root MSE     =    .16508

```

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x8	-.0029339	.0197854	-0.15	0.888	-.0537938	.047926
x10	.0910627	.0202899	4.49	0.006	.0389058	.1432196
x12	-.0582554	.0081802	-7.12	0.001	-.0792832	-.0372276
x18	.0891009	.0200077	4.45	0.007	.0376694	.1405323
x19	-.1018128	.0193191	-5.27	0.003	-.1514742	-.0521515
x20	.0740387	.0086312	8.58	0.000	.0518516	.0962258
y192	-3.71895	.5068204	-7.34	0.001	-5.021774	-2.416127
y193	2.937665	.7332999	4.01	0.010	1.052658	4.822673
_cons	-.0237019	.0100877	-2.35	0.066	-.0496331	.0022292

```

. test y192 y193
( 1) y192 = 0
( 2) y193 = 0
      F( 2, 2255) = 149.38
      Prob > F = 0.0000

```

. \*20 test all actual variables and diff. variables snow

. reg lnb x14 x21,robust cluster(PD)

Linear regression

Number of obs =	2262
F( 2, 5) =	15.97
Prob > F =	0.0067
R-squared =	0.0858
Root MSE =	.19684

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x14	-1.49e-06	7.04e-07	-2.11	0.088	-3.30e-06	3.21e-07
x21	4.54e-06	1.02e-06	4.44	0.007	1.91e-06	7.16e-06
_cons	.0936507	.0241033	3.89	0.012	.0316911	.1556102

. predict u20,r

. predict y20hat,xb

. reg lnb x14 x21 l.u20,robust cluster(PD)

Linear regression

Number of obs =	2256
F( 3, 5) =	50.76
Prob > F =	0.0004
R-squared =	0.1365
Root MSE =	.19157

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x14	-1.09e-06	6.41e-07	-1.71	0.149	-2.74e-06	5.54e-07
x21	4.81e-06	8.72e-07	5.52	0.003	2.57e-06	7.05e-06
u20	.2482193	.0340531	7.29	0.001	.1606831	.3357555
_cons	.0818197	.0214268	3.82	0.012	.0267404	.136899

. gen y202=y20hat\*y20hat

. gen y203=y202\*y20hat

. reg lnb x14 x21 y202 y203, robust cluster(PD)

Linear regression

Number of obs =	2262
F( 4, 5) =	2588.05
Prob > F =	0.0000
R-squared =	0.1158
Root MSE =	.19367

(Std. Err. adjusted for 6 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x14	-1.31e-06	6.60e-07	-1.99	0.103	-3.01e-06	3.84e-07
x21	4.24e-06	1.23e-06	3.46	0.018	1.09e-06	7.40e-06
y202	7.207396	1.933699	3.73	0.014	2.236665	12.17813
y203	1.050463	12.63953	0.08	0.937	-31.44049	33.54142
_cons	.0425986	.0225888	1.89	0.118	-.0154679	.100665

. test y202 y203

( 1) y202 = 0

( 2) y203 = 0

F( 2, 5) =	18.66
Prob > F =	0.0048

## Quarter

```
. xtfisher ln b, lags(5)
```

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

```
chi2(16) = 614.9126
Prob > chi2 = 0.0000
```

```
. xtfisher x1, lags(5)
```

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

```
chi2(16) = 809.1603
Prob > chi2 = 0.0000
```

```
. xtfisher x2, lags(5)
```

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

```
chi2(16) = 773.7495
Prob > chi2 = 0.0000
```

```
. xtfisher x3, lags(5)
```

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

```
chi2(16) = 845.2670
Prob > chi2 = 0.0000
```

```
. xtfisher x4, lags(5)
```

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

```
chi2(16) = 855.8663
Prob > chi2 = 0.0000
```

```
. xtfisher x5, lags(5)
```

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

```
chi2(16) = 744.5173
Prob > chi2 = 0.0000
```

```
. xtfisher x6, lags(5)
```

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

```
chi2(16) = 727.4993
Prob > chi2 = 0.0000
```

. xtfisher x7, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(16) = 851.2741  
Prob > chi2 = 0.0000

. xtfisher x8, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(16) = 738.5779  
Prob > chi2 = 0.0000

. xtfisher x9, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(16) = 827.2487  
Prob > chi2 = 0.0000

. xtfisher x10, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(16) = 728.7316  
Prob > chi2 = 0.0000

. xtfisher x11, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(16) = 596.9476  
Prob > chi2 = 0.0000

. xtfisher x12, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(16) = 512.1145  
Prob > chi2 = 0.0000

. xtfisher x13, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(16) = 842.3151  
Prob > chi2 = 0.0000

. xtfisher x14, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(16) = 719.5916  
Prob > chi2 = 0.0000

. xtfisher x15, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(16) = 427.2065  
Prob > chi2 = 0.0000

. xtfisher x16, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(16) = 418.7913  
Prob > chi2 = 0.0000

. xtfisher x17, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(16) = 500.4986  
Prob > chi2 = 0.0000

. xtfisher x18, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(16) = 312.8978  
Prob > chi2 = 0.0000

. xtfisher x19, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(16) = 376.8111  
Prob > chi2 = 0.0000

. xtfisher x20, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(16) = 383.0151  
Prob > chi2 = 0.0000

. xtfisher x21, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(16) = 365.9931  
Prob > chi2 = 0.0000

. \*1 test actual variables

. reg lnb x2 x4 x6 x8 x10 x12 x14,robust cluster(PD)

Linear regression

Number of obs = 2472  
 F( 6, 7) = .  
 Prob > F = .  
 R-squared = 0.1663  
 Root MSE = .26785

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	.0015685	.0002871	5.46	0.001	.0008895	.0022474
x4	-.0002046	.0002726	-0.75	0.477	-.0008491	.00044
x6	-.0021606	.0002313	-9.34	0.000	-.0027075	-.0016136
x8	.01684	.001346	12.51	0.000	.0136572	.0200227
x10	-.0050429	.0006978	-7.23	0.000	-.0066931	-.0033928
x12	.002963	.0002567	11.54	0.000	.0023559	.0035701
x14	3.76e-07	6.35e-08	5.92	0.001	2.26e-07	5.26e-07
_cons	.0266432	.0633091	0.42	0.686	-.1230591	.1763455

. test x2 x4 x6

- ( 1) x2 = 0
- ( 2) x4 = 0
- ( 3) x6 = 0

F( 3, 7) = 51.12  
 Prob > F = 0.0000

. test x8 x10 x12

- ( 1) x8 = 0
- ( 2) x10 = 0
- ( 3) x12 = 0

F( 3, 7) = 56.31  
 Prob > F = 0.0000

. predict u,r

. predict yhat,xb

. reg lnb x2 x4 x6 x8 x10 x12 x14 l.u,robust cluster(PD)

Linear regression

Number of obs = 2464  
 F( 6, 7) = .  
 Prob > F = .  
 R-squared = 0.1677  
 Root MSE = .26807

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	.0016706	.0002828	5.91	0.001	.0010018	.0023393
x4	-.0003151	.0002606	-1.21	0.266	-.0009314	.0003011
x6	-.0021495	.0002232	-9.63	0.000	-.0026773	-.0016217
x8	.0166757	.0012625	13.21	0.000	.0136905	.0196609
x10	-.0046962	.0005866	-8.01	0.000	-.0060832	-.0033091
x12	.0028247	.0001954	14.46	0.000	.0023627	.0032866
x14	3.63e-07	6.15e-08	5.90	0.001	2.17e-07	5.08e-07
u						
l1.	.0429989	.0272026	1.58	0.158	-.0213251	.1073228
_cons	.0243848	.0606058	0.40	0.699	-.1189251	.1676947



```

. gen y2=yhat*yhat
.
. gen y3=y2*yhat
.
. reg lnb x2 x4 x6 x8 x10 x12 x14 y2 y3, robust cluster(PD)
Linear regression                               Number of obs =   2472
                                                F( 6,          7) =    .
                                                Prob > F       =    .
                                                R-squared     =  0.1865
                                                Root MSE     =  0.2647

```

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	.0019294	.0002801	6.89	0.000	.001267	.0025917
x4	-.0003056	.0002486	-1.23	0.259	-.0008934	.0002821
x6	-.0026583	.0002804	-9.48	0.000	-.0033214	-.0019953
x8	.0252747	.002604	9.71	0.000	.0191172	.0314323
x10	-.0082477	.0010927	-7.55	0.000	-.0108316	-.0056639
x12	.004091	.0004168	9.82	0.000	.0031054	.0050766
x14	4.96e-07	5.30e-08	9.36	0.000	3.71e-07	6.22e-07
y2	-.7572217	.5265451	-1.44	0.194	-2.002303	.4878597
y3	-1.267625	.8215661	-1.54	0.167	-3.21032	.6750698
_cons	.0167497	.0624784	0.27	0.796	-.1309883	.1644877

```

. test y2 y3
( 1) y2 = 0
( 2) y3 = 0
      F( 2,          7) =  10.42
      Prob > F =  0.0080

```

. \*2 test actual variables reservoir level

. reg lnb x2 x4 x6,robust cluster(PD)

Linear regression

Number of obs = 2472  
 F( 3, 7) = 1.69  
 Prob > F = 0.2554  
 R-squared = 0.0091  
 Root MSE = .29179

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	.0002628	.0002529	1.04	0.333	-.0003351	.0008608
x4	-.0001504	.0002164	-0.69	0.510	-.0006622	.0003614
x6	.0000603	.000177	0.34	0.743	-.0003583	.0004789
_cons	.0274143	.0633196	0.43	0.678	-.1223127	.1771412

. predict u2,r

. predict y2hat,xb

. reg lnb x2 x4 x6 l.u2,robust cluster(PD)

Linear regression

Number of obs = 2464  
 F( 4, 7) = 4.61  
 Prob > F = 0.0387  
 R-squared = 0.0118  
 Root MSE = .29187

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	.0003928	.0002402	1.64	0.146	-.0001751	.0009607
x4	-.0002585	.0002072	-1.25	0.252	-.0007486	.0002315
x6	.0000394	.000173	0.23	0.826	-.0003698	.0004485
u2	.053768	.0247345	2.17	0.066	-.0047198	.1122558
_cons	.0247487	.0598518	0.41	0.692	-.1167782	.1662756

. gen y22=y2hat\*y2hat

. gen y23=y22\*y2hat

. reg lnb x2 x4 x6 y22 y23, robust cluster(PD)

Linear regression

Number of obs = 2472  
 F( 5, 7) = 1.23  
 Prob > F = 0.3855  
 R-squared = 0.0123  
 Root MSE = .29143

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	.0002892	.0052609	0.05	0.958	-.0121507	.0127292
x4	-.0001957	.0029731	-0.07	0.949	-.0072259	.0068346
x6	.000169	.0011518	0.15	0.887	-.0025546	.0028926
y22	-26.74361	277.6026	-0.10	0.926	-683.1694	629.6822
y23	185.2096	1146.754	0.16	0.876	-2526.434	2896.853
_cons	.0630122	.1602316	0.39	0.706	-.3158755	.4418998

. test y22 y23

- ( 1) y22 = 0
- ( 2) y23 = 0

F( 2, 7) = 0.23  
 Prob > F = 0.8015

. \*3 test actual variables inflow

. reg lnb x8 x10 x12,robust cluster(PD)

Linear regression

Number of obs =	2472
F( 3, 7) =	21.85
Prob > F =	0.0006
R-squared =	0.0858
Root MSE =	.28026

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x8	.0106165	.0019736	5.38	0.001	.0059496	.0152835
x10	-.0043375	.0009878	-4.39	0.003	-.0066734	-.0020016
x12	.0016637	.0008275	2.01	0.084	-.000293	.0036205
_cons	-.0112383	.0435998	-0.26	0.804	-.1143354	.0918588

. predict u3, r

. predict y3hat,xb

. reg lnb x8 x10 x12 l.u3,robust cluster(PD)

Linear regression

Number of obs =	2464
F( 4, 7) =	22.27
Prob > F =	0.0004
R-squared =	0.0865
Root MSE =	.28062

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x8	.0106216	.0019269	5.51	0.001	.0060653	.015178
x10	-.0042839	.00103	-4.16	0.004	-.0067194	-.0018483
x12	.0016242	.0008547	1.90	0.099	-.0003969	.0036452
u3						
L1.	.0303361	.0448641	0.68	0.521	-.0757506	.1364228
_cons	-.0114336	.0421816	-0.27	0.794	-.1111772	.0883099

. gen y32=y3hat\*y3hat

. gen y33=y32\*y3hat

. reg lnb x8 x10 x12 y32 y33, robust cluster(PD)

Linear regression

Number of obs =	2472
F( 5, 7) =	87.78
Prob > F =	0.0000
R-squared =	0.0968
Root MSE =	.27868

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x8	.0217353	.0063213	3.44	0.011	.0067879	.0366827
x10	-.009051	.0026268	-3.45	0.011	-.0152623	-.0028396
x12	.0031094	.0011468	2.71	0.030	.0003977	.005821
y32	-4.21701	2.777046	-1.52	0.173	-10.78368	2.349659
y33	2.960243	3.696938	0.80	0.450	-5.781627	11.70211
_cons	-.0477167	.0454332	-1.05	0.328	-.155149	.0597157

. test y32 y33

( 1) y32 = 0  
( 2) y33 = 0

F( 2, 7) =	3.08
Prob > F =	0.1096

. \*4 test actual variables snow

. reg lnb x14,robust cluster(PD)

Linear regression

Number of obs =	2472
F( 1, 7) =	11.86
Prob > F =	0.0108
R-squared =	0.0197
Root MSE =	.2901

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x14	2.47e-07	7.16e-08	3.44	0.011	7.73e-08	4.16e-07
_cons	.0388297	.0326382	1.19	0.273	-.0383475	.1160068

. predict u4,r

. predict y4hat,xb

. reg lnb x14 l.u4,robust cluster(PD)

Linear regression

Number of obs =	2464
F( 2, 7) =	7.84
Prob > F =	0.0163
R-squared =	0.0205
Root MSE =	.29045

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x14	2.54e-07	6.95e-08	3.65	0.008	8.91e-08	4.18e-07
u4	.0287936	.0254788	1.13	0.296	-.0314542	.0890415
_cons	.0381767	.0313918	1.22	0.263	-.036053	.1124065

. gen y42=y4hat\*y4hat

. gen y43=y42\*y4hat

. reg lnb x14 y42 y43, robust cluster(PD)

Linear regression

Number of obs =	2472
F( 3, 7) =	12.57
Prob > F =	0.0033
R-squared =	0.0363
Root MSE =	.28774

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x14	-2.09e-06	1.27e-06	-1.65	0.144	-5.10e-06	9.15e-07
y42	101.5999	48.77112	2.08	0.076	-13.72553	216.9252
y43	-307.5591	130.0535	-2.36	0.050	-615.0867	-.0314043
_cons	-.0839997	.0702743	-1.20	0.271	-.250172	.0821727

. test y42 y43

( 1) y42 = 0  
( 2) y43 = 0

F( 2, 7) =	7.42
Prob > F =	0.0186

. \*5 Test all seasonal variables

. reg lnb x1 x3 x5 x7 x9 x11 x13,robust cluster(PD)

Linear regression Number of obs = 2472  
F( 6, 7) = .  
Prob > F = .  
R-squared = 0.0545  
Root MSE = .28525

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	.0002011	.0009263	0.22	0.834	-.0019892	.0023914
x3	.0001061	.0016255	0.07	0.950	-.0037375	.0039497
x5	-.0007028	.0006701	-1.05	0.329	-.0022874	.0008819
x7	-.0068183	.0007352	-9.27	0.000	-.0085567	-.0050799
x9	.0149796	.0012279	12.20	0.000	.0120761	.0178832
x11	-.0055662	.000795	-7.00	0.000	-.0074461	-.0036863
x13	9.43e-08	3.57e-07	0.26	0.799	-7.50e-07	9.39e-07
_cons	.0842958	.0611223	1.38	0.210	-.0602353	.228827

. test x1 x3 x5

- ( 1) x1 = 0
- ( 2) x3 = 0
- ( 3) x5 = 0

F( 3, 7) = 19.08  
Prob > F = 0.0010

. test x7 x9 x11

- ( 1) x7 = 0
- ( 2) x9 = 0
- ( 3) x11 = 0

F( 3, 7) = 113.84  
Prob > F = 0.0000

. predict u5,r

. predict y5hat,xb

. reg lnb x1 x3 x5 x7 x9 x11 x13 l.u5,robust cluster(PD)

Linear regression Number of obs = 2464  
F( 6, 7) = .  
Prob > F = .  
R-squared = 0.0556  
Root MSE = .28555

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	.0001191	.0009	0.13	0.898	-.002009	.0022472
x3	.0003214	.0015947	0.20	0.846	-.0034496	.0040923
x5	-.0008502	.0006667	-1.28	0.243	-.0024268	.0007264
x7	-.0070264	.0006783	-10.36	0.000	-.0086303	-.0054226
x9	.0152925	.0011588	13.20	0.000	.0125525	.0180325
x11	-.0056267	.0007863	-7.16	0.000	-.0074861	-.0037673
x13	1.45e-07	3.53e-07	0.41	0.695	-6.91e-07	9.80e-07
u5						
l1.	-.0366329	.022429	-1.63	0.146	-.0896691	.0164032
_cons	.0841453	.0635274	1.32	0.227	-.0660731	.2343637

```

. gen y52=y5hat*y5hat
.
. gen y53=y52*y5hat
.
. reg lnb x1 x3 x5 x7 x9 x11 x13 y52 y53, robust cluster(PD)
Linear regression                               Number of obs = 2472
                                                F( 6, 7) = .
                                                Prob > F = .
                                                R-squared = 0.0760
                                                Root MSE = .2821

```

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	.0008825	.0008988	0.98	0.359	-.0012427	.0030078
x3	-.0011831	.0015718	-0.75	0.476	-.0048999	.0025336
x5	.0000786	.0006707	0.12	0.910	-.0015074	.0016647
x7	-.0148475	.0026604	-5.58	0.001	-.0211384	-.0085566
x9	.0230332	.0037295	6.18	0.000	.0142143	.0318522
x11	-.008806	.0014414	-6.11	0.000	-.0122145	-.0053975
x13	-1.29e-07	3.48e-07	-0.37	0.722	-9.52e-07	6.94e-07
y52	9.508213	2.672681	3.56	0.009	3.188326	15.8281
y53	-39.51874	6.671406	-5.92	0.001	-55.2941	-23.74337
_cons	.0341466	.0588373	0.58	0.580	-.1049816	.1732748

```

. test y52 y53
( 1) y52 = 0
( 2) y53 = 0
      F( 2, 7) = 24.58
      Prob > F = 0.0007

```

. \*6 Test all seasonal variables reservoir level

. reg lnb x1 x3 x5,robust cluster(PD)

Linear regression

Number of obs = 2472  
 F( 3, 7) = 25.92  
 Prob > F = 0.0004  
 R-squared = 0.0417  
 Root MSE = .28695

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	-.0021477	.0004064	-5.29	0.001	-.0031086	-.0011868
x3	.0009915	.0004075	2.43	0.045	.000028	.001955
x5	.0012369	.0002664	4.64	0.002	.0006068	.0018669
_cons	.0895202	.0604748	1.48	0.182	-.05348	.2325205

. predict u6,r

. predict y6hat,xb

. reg lnb x1 x3 x5 l.u6,robust cluster(PD)

Linear regression

Number of obs = 2464  
 F( 4, 7) = 233.90  
 Prob > F = 0.0000  
 R-squared = 0.0419  
 Root MSE = .28739

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	-.0021547	.0004084	-5.28	0.001	-.0031204	-.001189
x3	.0009936	.0004139	2.40	0.047	.0000148	.0019725
x5	.0012426	.0002648	4.69	0.002	.0006165	.0018688
u6	-.0171198	.022333	-0.77	0.468	-.0699289	.0356892
_cons	.0896127	.0616153	1.45	0.189	-.0560843	.2353097

. gen y62=y6hat\*y6hat

. gen y63=y62\*y6hat

. reg lnb x1 x3 x5 y62 y63, robust cluster(PD)

Linear regression

Number of obs = 2472  
 F( 5, 7) = 237.21  
 Prob > F = 0.0000  
 R-squared = 0.0536  
 Root MSE = .28526

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	-.001027	.0006478	-1.59	0.157	-.0025588	.0005049
x3	.000294	.0003809	0.77	0.465	-.0006067	.0011947
x5	.0008246	.0005423	1.52	0.172	-.0004577	.0021069
y62	12.71205	2.712541	4.69	0.002	6.297913	19.1262
y63	-45.50966	6.818546	-6.67	0.000	-61.63296	-29.38636
_cons	.0181781	.0561679	0.32	0.756	-.1146379	.1509942

. test y62 y63

( 1) y62 = 0  
 ( 2) y63 = 0

F( 2, 7) = 28.55  
 Prob > F = 0.0004

. \*7 Test all seasonal variables inflow

. reg ln b x7 x9 x11,robust cluster(PD)

Linear regression Number of obs = 2472  
F( 3, 7) = 32.08  
Prob > F = 0.0002  
R-squared = 0.0458  
Root MSE = .28632

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x7	-.0206372	.0090498	-2.28	0.057	-.0420365	.0007621
x9	.024839	.0082514	3.01	0.020	.0053274	.0443506
x11	-.0090996	.0035638	-2.55	0.038	-.0175267	-.0006726
_cons	.061793	.0466941	1.32	0.227	-.0486211	.1722071

. predict u7,r

. predict y7hat,xb

. reg ln b x7 x9 x11 l.u7,robust cluster(PD)

Linear regression Number of obs = 2464  
F( 4, 7) = 173.19  
Prob > F = 0.0000  
R-squared = 0.0463  
Root MSE = .28673

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x7	-.0209073	.0091248	-2.29	0.056	-.042484	.0006695
x9	.0251287	.0082742	3.04	0.019	.0055634	.044694
x11	-.0091889	.0035946	-2.56	0.038	-.0176888	-.0006891
u7						
L1.	-.0248085	.0241862	-1.03	0.339	-.0819998	.0323828
_cons	.0618525	.0480074	1.29	0.239	-.051667	.1753719

. gen y72=y7hat\*y7hat

. gen y73=y72\*y7hat

. reg ln b x7 x9 x11 y72 y73, robust cluster(PD)

Linear regression Number of obs = 2472  
F( 5, 7) = 278.91  
Prob > F = 0.0000  
R-squared = 0.0611  
Root MSE = .28414

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x7	-.0337307	.014354	-2.35	0.051	-.0676727	.0002112
x9	.0401952	.0153325	2.62	0.034	.0039395	.0764508
x11	-.0138329	.0059481	-2.33	0.053	-.027898	.0002321
y72	1.086576	2.449762	0.44	0.671	-4.706192	6.879343
y73	-13.46489	3.175194	-4.24	0.004	-20.97303	-5.956748
_cons	.0585856	.0500447	1.17	0.280	-.0597513	.1769225

. test y72 y73

( 1) y72 = 0

( 2) y73 = 0

F( 2, 7) = 133.39  
Prob > F = 0.0000



. \*8 Test all seasonal variables snow

. reg lnb x13,robust cluster(PD)

Linear regression

Number of obs = 2472  
 F( 1, 7) = 0.45  
 Prob > F = 0.5237  
 R-squared = 0.0009  
 Root MSE = .29287

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x13	6.22e-08	9.27e-08	0.67	0.524	-1.57e-07	2.81e-07
_cons	.0642346	.0340183	1.89	0.101	-.0162058	.144675

. predict u8,r

. predict y8hat,xb

. reg lnb x13 l.u8,robust cluster(PD)

Linear regression

Number of obs = 2464  
 F( 2, 7) = 1.30  
 Prob > F = 0.3319  
 R-squared = 0.0018  
 Root MSE = .29322

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x13	6.77e-08	9.00e-08	0.75	0.477	-1.45e-07	2.81e-07
u8	.0294546	.0215857	1.36	0.215	-.0215876	.0804968
_cons	.0638159	.0328986	1.94	0.094	-.013977	.1416088

. gen y82=y8hat\*y8hat

. gen y83=y82\*y8hat

. reg lnb x13 y82 y83, robust cluster(PD)

Linear regression

Number of obs = 2472  
 F( 3, 7) = 7.06  
 Prob > F = 0.0160  
 R-squared = 0.0055  
 Root MSE = .29231

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x13	-.0000257	.000013	-1.97	0.089	-.0000566	5.12e-06
y82	5275.248	2582.579	2.04	0.080	-831.5804	11382.08
y83	-22140.97	10446.15	-2.12	0.072	-46842.18	2560.236
_cons	-15.82062	7.888791	-2.01	0.085	-34.47464	2.833408

. test y82 y83

( 1) y82 = 0  
 ( 2) y83 = 0

F( 2, 7) = 8.46  
 Prob > F = 0.0136

. \*9 test all actual and season variables

. reg lnb x1 x2 x3 x4 x5 x6 x7 x8 x9 x10 x11 x12 x13 x14,robust cluster(PD)

Linear regression

Number of obs = 2472  
 F( 6, 7) = .  
 Prob > F = .  
 R-squared = 0.5039  
 Root MSE = .20692

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	-.0124392	.0012654	-9.83	0.000	-.0154314	-.009447
x2	.0037075	.0002838	13.07	0.000	.0030365	.0043785
x3	.0137961	.0017766	7.77	0.000	.0095952	.017997
x4	.0015609	.0003183	4.90	0.002	.0008081	.0023136
x5	-.0066794	.0008911	-7.50	0.000	-.0087864	-.0045724
x6	-.0004951	.000154	-3.22	0.015	-.0008592	-.000131
x7	-.0084134	.0021647	-3.89	0.006	-.0135321	-.0032947
x8	.0066309	.0008991	7.37	0.000	.0045047	.008757
x9	.0050715	.0021085	2.41	0.047	.0000857	.0100572
x10	-.0009059	.0002198	-4.12	0.004	-.0014257	-.0003861
x11	.0007058	.0008059	0.88	0.410	-.0011998	.0026114
x12	.000201	.0004047	0.50	0.635	-.0007561	.001158
x13	2.49e-06	5.57e-07	4.47	0.003	1.17e-06	3.81e-06
x14	4.81e-07	1.64e-07	2.94	0.022	9.43e-08	8.68e-07
_cons	.0986701	.0636734	1.55	0.165	-.0518935	.2492338

. test x1 x2 x3 x4 x5 x6

- ( 1) x1 = 0
- ( 2) x2 = 0
- ( 3) x3 = 0
- ( 4) x4 = 0
- ( 5) x5 = 0
- ( 6) x6 = 0

F( 6, 7) = 128.38  
 Prob > F = 0.0000

. test x1 x3 x5

- ( 1) x1 = 0
- ( 2) x3 = 0
- ( 3) x5 = 0

F( 3, 7) = 51.02  
 Prob > F = 0.0000

. test x2 x3 x5

- ( 1) x2 = 0
- ( 2) x3 = 0
- ( 3) x5 = 0

F( 3, 7) = 57.10  
 Prob > F = 0.0000

. test x7 x8 x9 x10 x11 x12

- ( 1) x7 = 0
- ( 2) x8 = 0
- ( 3) x9 = 0
- ( 4) x10 = 0
- ( 5) x11 = 0
- ( 6) x12 = 0

F( 6, 7) = 39.83  
 Prob > F = 0.0000

. test x7 x9 x11

- ( 1) x7 = 0
- ( 2) x9 = 0
- ( 3) x11 = 0

F( 3, 7) = 8.75  
 Prob > F = 0.0091

. test x8 x10 x12

- ( 1) x8 = 0
- ( 2) x10 = 0
- ( 3) x12 = 0

F( 3, 7) = 21.92  
 Prob > F = 0.0006

. test x13 x14

- ( 1) x13 = 0
- ( 2) x14 = 0

F( 2, 7) = 90.29  
 Prob > F = 0.0000

```

. predict u9,r
.
. predict y9hat,xb
.
. reg lnb x1 x2 x3 x4 x5 x6 x7 x8 x9 x10 x11 x12 x13 x14 l.u9,robust cluster(PD)

```

Linear regression

Number of obs =	2464
F( 6, 7) =	.
Prob > F =	.
R-squared =	0.5184
Root MSE =	.20421

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	-.0130817	.001322	-9.90	0.000	-.0162078	-.0099556
x2	.0041996	.0004143	10.14	0.000	.0032199	.0051793
x3	.0141923	.0017985	7.89	0.000	.0099395	.0184452
x4	.0011937	.0003559	3.35	0.012	.0003521	.0020353
x5	-.0064417	.0008119	-7.93	0.000	-.0083615	-.0045218
x6	-.0005912	.0001296	-4.56	0.003	-.0008976	-.0002848
x7	-.0060812	.0019596	-3.10	0.017	-.0107149	-.0014475
x8	.0057069	.0006927	8.24	0.000	.0040689	.0073448
x9	.0023823	.0017054	1.40	0.205	-.0016502	.0064148
x10	.0001637	.0003195	0.51	0.624	-.0005918	.0009193
x11	.0014488	.000667	2.17	0.066	-.0001283	.0030259
x12	-.0001928	.0004906	-0.39	0.706	-.0013528	.0009672
x13	2.50e-06	5.16e-07	4.85	0.002	1.28e-06	3.72e-06
x14	4.69e-07	1.46e-07	3.22	0.015	1.25e-07	8.14e-07
u9						
_l1.	.177195	.0428428	4.14	0.004	.0758879	.2785022
_cons	.1015262	.0520815	1.95	0.092	-.0216271	.2246794

```

. gen y92=y9hat*y9hat
.
. gen y93=y92*y9hat
.
. reg lnb x1 x2 x3 x4 x5 x6 x7 x8 x9 x10 x11 x12 x13 x14 y92 y93, robust cluster(> PD)

```

Linear regression

Number of obs =	2472
F( 7, 7) =	.
Prob > F =	.
R-squared =	0.5177
Root MSE =	.2041

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	-.0115536	.0015926	-7.25	0.000	-.0153195	-.0077878
x2	.004095	.0004753	8.61	0.000	.002971	.005219
x3	.0119503	.0019658	6.08	0.001	.0073019	.0165987
x4	.001422	.0003759	3.78	0.007	.0005332	.0023109
x5	-.0062473	.0011268	-5.54	0.001	-.0089117	-.0035828
x6	-.0003526	.0001568	-2.25	0.059	-.0007233	.0000182
x7	-.0059382	.0020386	-2.91	0.023	-.0107587	-.0011177
x8	.0042093	.0016351	2.57	0.037	.0003429	.0080758
x9	.0055196	.0019163	2.88	0.024	.0009883	.010051
x10	.0002753	.0004798	0.57	0.584	-.0008593	.0014099
x11	-.000837	.0006155	-1.36	0.216	-.0022925	.0006184
x12	.00052	.0004657	1.12	0.301	-.0005812	.0016212
x13	2.09e-06	5.94e-07	3.52	0.010	6.87e-07	3.50e-06
x14	4.95e-07	1.52e-07	3.25	0.014	1.35e-07	8.55e-07
y92	.5364857	.1098104	4.89	0.002	.2768253	.7961461
y93	-.3632036	.497731	-0.73	0.489	-1.540151	.8137433
_cons	.1037898	.0627441	1.65	0.142	-.0445764	.2521559

```

. test y92 y93

```

- ( 1) y92 = 0
- ( 2) y93 = 0

F( 2, 7) = 17.80  
 Prob > F = 0.0018

. \*10 test all actual and season variables reservoir level

. reg lnb x1 x2 x3 x4 x5 x6,robust cluster(PD)

Linear regression

Number of obs =	2472
F( 6, 7) =	80.01
Prob > F =	0.0000
R-squared =	0.4536
Root MSE =	.2168

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	-.0063951	.0004796	-13.33	0.000	-.0075292	-.0052609
x2	.0037769	.0003063	12.33	0.000	.0030525	.0045012
x3	-.0001861	.0002236	-0.83	0.433	-.0007149	.0003427
x4	.0018916	.0002918	6.48	0.000	.0012015	.0025816
x5	.0013875	.0002683	5.17	0.001	.0007529	.002022
x6	-.0003751	.0001391	-2.70	0.031	-.000704	-.0000463
_cons	.1016779	.0601776	1.69	0.135	-.0406195	.2439753

. test x1 x3 x5

( 1) x1 = 0  
 ( 2) x3 = 0  
 ( 3) x5 = 0

F( 3, 7) = 61.82  
 Prob > F = 0.0000

. test x2 x4 x6

( 1) x2 = 0  
 ( 2) x4 = 0  
 ( 3) x6 = 0

F( 3, 7) = 66.05  
 Prob > F = 0.0000

. predict u10,r

. predict y10hat,xb

. reg lnb x1 x2 x3 x4 x5 x6 l.u10,robust cluster(PD)

Linear regression

Number of obs =	2464
F( 6, 7) =	.
Prob > F =	.
R-squared =	0.4750
Root MSE =	.21286

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	-.0066541	.0004411	-15.08	0.000	-.0076972	-.0056111
x2	.004248	.0004075	10.42	0.000	.0032844	.0052116
x3	-.0000912	.000178	-0.51	0.624	-.0005121	.0003297
x4	.0015919	.0003305	4.82	0.002	.0008104	.0023733
x5	.0014805	.0002543	5.82	0.001	.0008793	.0020818
x6	-.0005043	.0001192	-4.23	0.004	-.0007861	-.0002225
u10						
l1.	.1990161	.0390138	5.10	0.001	.106763	.2912691
_cons	.1044659	.0476555	2.19	0.064	-.0082214	.2171533

```

. gen y102=y10hat*y10hat
.
. gen y103=y102*y10hat
.
. reg lnb x1 x2 x3 x4 x5 x6 y102 y103, robust cluster(PD)
Linear regression                               Number of obs =    2472
                                                F( 6,          7) =    .
                                                Prob > F       =    .
                                                R-squared     =    0.4705
                                                Root MSE     =    .2135

```

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	-.0065135	.0009675	-6.73	0.000	-.0088013	-.0042256
x2	.0039478	.0005747	6.87	0.000	.0025889	.0053068
x3	.0000342	.0001998	0.17	0.869	-.0004382	.0005066
x4	.0016203	.0003159	5.13	0.001	.0008734	.0023672
x5	.0009713	.0002582	3.76	0.007	.0003608	.0015817
x6	-.0001093	.0001044	-1.05	0.330	-.0003561	.0001376
y102	.6843985	.1286856	5.32	0.001	.3801054	.9886916
y103	-.12201	.6063351	-0.20	0.846	-1.555765	1.311745
_cons	.1052314	.0595092	1.77	0.120	-.0354854	.2459482

```

. test y102 y103
( 1) y102 = 0
( 2) y103 = 0
      F( 2,          7) =    16.93
      Prob > F =    0.0021

```

```
. *11 test all actual and season variables inflow
.
. reg lnb x7 x8 x9 x10 x11 x12,robust cluster(PD)
```

Linear regression Number of obs = 2472  
F( 6, 7) = 74.92  
Prob > F = 0.0000  
R-squared = 0.1723  
Root MSE = .26683

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x7	-.0477145	.0094779	-5.03	0.002	-.0701263	-.0253027
x8	.0232969	.0018887	12.34	0.000	.0188309	.0277629
x9	.0341763	.0082514	4.14	0.004	.0146647	.0536878
x10	-.0065467	.0007401	-8.85	0.000	-.0082969	-.0047965
x11	-.0131373	.0033028	-3.98	0.005	-.0209471	-.0053275
x12	.0033402	.0005163	6.47	0.000	.0021192	.0045612
_cons	.0598895	.0475215	1.26	0.248	-.052481	.17226

```
. test x7 x9 x11
```

- ( 1) x7 = 0
- ( 2) x9 = 0
- ( 3) x11 = 0

F( 3, 7) = 112.61  
Prob > F = 0.0000

```
. test x8 x10 x12
```

- ( 1) x8 = 0
- ( 2) x10 = 0
- ( 3) x12 = 0

F( 3, 7) = 65.01  
Prob > F = 0.0000

```
. predict u11,r
```

```
. predict y11hat,xb
```

```
. reg lnb x7 x8 x9 x10 x11 x12 l.u11,robust cluster(PD)
```

Linear regression Number of obs = 2464  
F( 6, 7) = .  
Prob > F = .  
R-squared = 0.1738  
Root MSE = .26703

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x7	-.0472544	.0088603	-5.33	0.001	-.0682057	-.0263032
x8	.023397	.0019304	12.12	0.000	.0188323	.0279618
x9	.0334204	.0075552	4.42	0.003	.0155553	.0512855
x10	-.0063371	.0007216	-8.78	0.000	-.0080435	-.0046306
x11	-.0129748	.0030842	-4.21	0.004	-.0202678	-.0056817
x12	.0033089	.0005132	6.45	0.000	.0020953	.0045225
u11						
l1.	.0455217	.0231772	1.96	0.090	-.0092837	.1003272
_cons	.0600797	.0454232	1.32	0.228	-.047329	.1674884

```

. gen y112=y11hat*y11hat
.
. gen y113=y112*y11hat
.
. reg lnb x7 x8 x9 x10 x11 x12 y112 y113, robust cluster(PD)
Linear regression                               Number of obs =    2472
                                                F( 6,          7) =    .
                                                Prob > F       =    .
                                                R-squared     =    0.2112
                                                Root MSE     =    .26059

```

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x7	-.0601818	.0099258	-6.06	0.001	-.0836526	-.036711
x8	.0286162	.0033101	8.65	0.000	.0207891	.0364433
x9	.0443604	.0085123	5.21	0.001	.024232	.0644888
x10	-.0082397	.0011407	-7.22	0.000	-.0109371	-.0055423
x11	-.019164	.0034219	-5.60	0.001	-.0272556	-.0110724
x12	.0066778	.0005194	12.86	0.000	.0054495	.0079061
y112	.3824298	.3566844	1.07	0.319	-.4609947	1.225854
y113	-2.216457	.3273876	-6.77	0.000	-2.990606	-1.442308
_cons	.0533116	.0474993	1.12	0.299	-.0590065	.1656296

```

. test y112 y113
( 1) y112 = 0
( 2) y113 = 0
      F( 2,          7) =    32.07
      Prob > F =    0.0003

```

. \*12 test all actual and season variables snow

. reg lnb x13 x14,robust cluster(PD)

Linear regression

Number of obs =	2472
F( 2, 7) =	157.95
Prob > F =	0.0000
R-squared =	0.1164
Root MSE =	.27547

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x13	-1.96e-06	1.78e-07	-11.04	0.000	-2.38e-06	-1.54e-06
x14	1.81e-06	1.03e-07	17.55	0.000	1.57e-06	2.06e-06
_cons	.0716266	.0342029	2.09	0.075	-.0092503	.1525036

. predict u12,r

. predict y12hat,xb

. reg lnb x13 x14 l.u12,robust cluster(PD)

Linear regression

Number of obs =	2464
F( 3, 7) =	272.31
Prob > F =	0.0000
R-squared =	0.1183
Root MSE =	.27564

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x13	-1.96e-06	1.71e-07	-11.50	0.000	-2.36e-06	-1.56e-06
x14	1.82e-06	1.05e-07	17.31	0.000	1.57e-06	2.06e-06
u12	.0468256	.0292994	1.60	0.154	-.0224565	.1161077
_cons	.0710398	.0325285	2.18	0.065	-.0058778	.1479574

. gen y122=y12hat\*y12hat

. gen y123=y122\*y12hat

. reg lnb x13 x14 y122 y123, robust cluster(PD)

Linear regression

Number of obs =	2472
F( 4, 7) =	195.03
Prob > F =	0.0000
R-squared =	0.1697
Root MSE =	.26715

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x13	-3.06e-06	2.81e-07	-10.90	0.000	-3.73e-06	-2.40e-06
x14	2.97e-06	1.85e-07	16.02	0.000	2.53e-06	3.41e-06
y122	-.6843289	.7945271	-0.86	0.418	-2.563087	1.194429
y123	-5.165944	2.235693	-2.31	0.054	-10.45252	.1206287
_cons	.0793833	.0346522	2.29	0.056	-.0025561	.1613228

. test y122 y123

( 1) y122 = 0

( 2) y123 = 0

F( 2, 7) =	45.67
Prob > F =	0.0001



. \*13 Test all diff. variables

. reg lnb x15 x16 x17 x18 x19 x20 x21,robust cluster(PD)

Linear regression

Number of obs =	2472
F( 6, 7) =	.
Prob > F =	.
R-squared =	0.4302
Root MSE =	.22143

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x15	.0032955	.000192	17.17	0.000	.0028416	.0037494
x16	.0016903	.0003257	5.19	0.001	.0009202	.0024603
x17	-.0004574	.0001003	-4.56	0.003	-.0006946	-.0002202
x18	.0079133	.0012462	6.35	0.000	.0049665	.0108602
x19	-.0027517	.0007317	-3.76	0.007	-.0044819	-.0010216
x20	.0003602	.0004297	0.84	0.430	-.0006559	.0013764
x21	5.74e-07	8.08e-08	7.11	0.000	3.83e-07	7.65e-07
_cons	.0627539	.0298686	2.10	0.074	-.0078741	.1333818

. test x15 x16 x17

- ( 1) x15 = 0
- ( 2) x16 = 0
- ( 3) x17 = 0

F( 3, 7) = 99.24  
 Prob > F = 0.0000

. test x18 x19 x20

- ( 1) x18 = 0
- ( 2) x19 = 0
- ( 3) x20 = 0

F( 3, 7) = 24.15  
 Prob > F = 0.0005

. predict u13,r

. predict y13hat,xb

. reg lnb x15 x16 x17 x18 x19 x20 x21 l.u13,robust cluster(PD)

Linear regression

Number of obs =	2464
F( 6, 7) =	.
Prob > F =	.
R-squared =	0.4669
Root MSE =	.21455

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x15	.0040423	.0003086	13.10	0.000	.0033126	.0047721
x16	.0010589	.0003532	3.00	0.020	.0002237	.0018942
x17	-.0004464	.0001022	-4.37	0.003	-.000688	-.0002047
x18	.0056996	.0008729	6.53	0.000	.0036355	.0077637
x19	-.0003008	.0004639	-0.65	0.537	-.0013978	.0007962
x20	-.0003656	.0004616	-0.79	0.454	-.0014571	.000726
x21	5.99e-07	8.01e-08	7.48	0.000	4.09e-07	7.88e-07
u13						
l1.	.2628856	.0355471	7.40	0.000	.17883	.3469411
_cons	.0665062	.0220011	3.02	0.019	.0144819	.1185306

```

. gen y132=y13hat*y13hat
.
. gen y133=y132*y13hat
.
. reg lnb x15 x16 x17 x18 x19 x20 x21 y132 y133, robust cluster(PD)
Linear regression                               Number of obs = 2472
                                                F( 6, 7) = .
                                                Prob > F = .
                                                R-squared = 0.4333
                                                Root MSE = .22093

```

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x15	.0035866	.0003886	9.23	0.000	.0026677	.0045055
x16	.0017099	.0005556	3.08	0.018	.0003962	.0030236
x17	-.0003625	.0001078	-3.36	0.012	-.0006174	-.0001076
x18	.0083597	.0029785	2.81	0.026	.0013166	.0154028
x19	-.0026906	.0013198	-2.04	0.081	-.0058114	.0004301
x20	.0003798	.0003895	0.98	0.362	-.0005412	.0013007
x21	5.72e-07	9.12e-08	6.27	0.000	3.56e-07	7.87e-07
y132	.2287593	.3297829	0.69	0.510	-.5510534	1.008572
y133	-.6732213	.8283602	-0.81	0.443	-2.631982	1.285539
_cons	.0566831	.0370056	1.53	0.169	-.0308213	.1441874

```

. test y132 y133
( 1) y132 = 0
( 2) y133 = 0
      F( 2, 7) = 0.84
      Prob > F = 0.4697

```

. \*14 Test diff. variables reservoir level

. reg lnb x15 x16 x17,robust cluster(PD)

Linear regression Number of obs = 2472  
F( 3, 7) = 63.05  
Prob > F = 0.0000  
R-squared = 0.4060  
Root MSE = .22591

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x15	.0035869	.0002723	13.17	0.000	.002943	.0042308
x16	.0020364	.0002574	7.91	0.000	.0014276	.0026451
x17	-.0003564	.0001188	-3.00	0.020	-.0006372	-.0000756
_cons	.0721084	.0293515	2.46	0.044	.002703	.1415137

. predict u14,r

. predict y14hat,xb

. reg lnb x15 x16 x17 l.u14,robust cluster(PD)

Linear regression Number of obs = 2464  
F( 4, 7) = 56.47  
Prob > F = 0.0000  
R-squared = 0.4470  
Root MSE = .21834

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x15	.0040963	.0003479	11.77	0.000	.0032736	.004919
x16	.001674	.0002978	5.62	0.001	.0009699	.0023781
x17	-.0003444	.0001011	-3.41	0.011	-.0005834	-.0001054
u14						
l1.	.2633275	.0321588	8.19	0.000	.1872841	.339371
_cons	.0735331	.0217183	3.39	0.012	.0221775	.1248886

. gen y142=y14hat\*y14hat

. gen y143=y142\*y14hat

. reg lnb x15 x16 x17 y142 y143, robust cluster(PD)

Linear regression Number of obs = 2472  
F( 5, 7) = 783.67  
Prob > F = 0.0000  
R-squared = 0.4095  
Root MSE = .22533

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x15	.0039369	.0004617	8.53	0.000	.0028452	.0050286
x16	.0021727	.0005196	4.18	0.004	.000944	.0034014
x17	-.0002431	.0001353	-1.80	0.116	-.0005632	.0000769
y142	.1433521	.3332216	0.43	0.680	-.6445918	.9312959
y143	-.8534776	.8773708	-0.97	0.363	-2.92813	1.221175
_cons	.0697201	.0381903	1.83	0.111	-.0205855	.1600258

. test y142 y143

( 1) y142 = 0

( 2) y143 = 0

F( 2, 7) = 1.13  
Prob > F = 0.3762

. \*15 Test diff. variables inflow

. reg lnb x18 x19 x20,robust cluster(PD)

Linear regression

Number of obs =	2472
F( 3, 7) =	67.93
Prob > F =	0.0000
R-squared =	0.1290
Root MSE =	.27355

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x18	.0231222	.0020857	11.09	0.000	.0181902	.0280543
x19	-.0073327	.0010401	-7.05	0.000	-.0097921	-.0048733
x20	.0044002	.000529	8.32	0.000	.0031492	.0056511
_cons	.0588045	.0315219	1.87	0.104	-.015733	.1333419

. predict u15,r

. predict y15hat,xb

. reg lnb x18 x19 x20 l.u15,robust cluster(PD)

Linear regression

Number of obs =	2464
F( 4, 7) =	49.88
Prob > F =	0.0000
R-squared =	0.1380
Root MSE =	.27259

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x18	.0231999	.0020836	11.13	0.000	.018273	.0281268
x19	-.0065784	.0010247	-6.42	0.000	-.0090014	-.0041554
x20	.004282	.0005223	8.20	0.000	.003047	.005517
u15						
l1.	.1044017	.0224892	4.64	0.002	.0512231	.1575802
_cons	.0592735	.0282317	2.10	0.074	-.0074838	.1260309

. gen y152=y15hat\*y15hat

. gen y153=y152\*y15hat

. reg lnb x15 x16 x17 y152 y153, robust cluster(PD)

Linear regression

Number of obs =	2472
F( 5, 7) =	279.51
Prob > F =	0.0000
R-squared =	0.4255
Root MSE =	.22226

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x15	.0034354	.0002524	13.61	0.000	.0028386	.0040322
x16	.0019735	.0002659	7.42	0.000	.0013447	.0026023
x17	-.0002891	.0001132	-2.55	0.038	-.0005567	-.0000214
y152	2.647283	.7243477	3.65	0.008	.9344731	4.360094
y153	-4.080452	1.13658	-3.59	0.009	-6.768037	-1.392868
_cons	.0457085	.0312974	1.46	0.188	-.0282982	.1197151

. test y152 y153

( 1) y152 = 0  
( 2) y153 = 0

F( 2, 7) = 6.68  
Prob > F = 0.0238

. \*16 Test diff. variables snow

. reg lnb x21,robust cluster(PD)

Linear regression

Number of obs = 2472  
 F( 1, 7) = 170.93  
 Prob > F = 0.0000  
 R-squared = 0.1117  
 Root MSE = .27615

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x21	<b>1.71e-06</b>	<b>1.31e-07</b>	<b>13.07</b>	<b>0.000</b>	<b>1.40e-06</b>	<b>2.02e-06</b>
_cons	<b>.0541556</b>	<b>.0308688</b>	<b>1.75</b>	<b>0.123</b>	<b>-.0188375</b>	<b>.1271488</b>

. predict u16,r

. predict y16hat,xb

. reg lnb x21 l.u16,robust cluster(PD)

Linear regression

Number of obs = 2464  
 F( 2, 7) = 127.16  
 Prob > F = 0.0000  
 R-squared = 0.1130  
 Root MSE = .2764

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x21	<b>1.71e-06</b>	<b>1.37e-07</b>	<b>12.56</b>	<b>0.000</b>	<b>1.39e-06</b>	<b>2.04e-06</b>
u16	<b>.0408768</b>	<b>.0296046</b>	<b>1.38</b>	<b>0.210</b>	<b>-.0291269</b>	<b>.1108806</b>
_cons	<b>.0540916</b>	<b>.0295811</b>	<b>1.83</b>	<b>0.110</b>	<b>-.0158564</b>	<b>.1240397</b>

. gen y162=y16hat\*y16hat

. gen y163=y162\*y16hat

. reg lnb x21 y162 y163, robust cluster(PD)

Linear regression

Number of obs = 2472  
 F( 3, 7) = 191.26  
 Prob > F = 0.0000  
 R-squared = 0.1847  
 Root MSE = .26466

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x21	<b>3.40e-06</b>	<b>3.84e-07</b>	<b>8.85</b>	<b>0.000</b>	<b>2.49e-06</b>	<b>4.31e-06</b>
y162	<b>-1.866368</b>	<b>1.927172</b>	<b>-0.97</b>	<b>0.365</b>	<b>-6.423407</b>	<b>2.690671</b>
y163	<b>-4.336286</b>	<b>3.478462</b>	<b>-1.25</b>	<b>0.253</b>	<b>-12.56154</b>	<b>3.88897</b>
_cons	<b>.0800464</b>	<b>.0332754</b>	<b>2.41</b>	<b>0.047</b>	<b>.0013625</b>	<b>.1587302</b>

. test y162 y163

( 1) **y162 = 0**

( 2) **y163 = 0**

F( 2, 7) = 21.47  
 Prob > F = 0.0010

. \*17 test all actual variables and diff. variables

. reg lnb x2 x4 x6 x8 x10 x12 x14 x15 x16 x17 x18 x19 x20 x21,robust cluster(PD)

Linear regression

Number of obs = 2472  
 F( 6, 7) = .  
 Prob > F = .  
 R-squared = 0.5040  
 Root MSE = .2069

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	-.0087558	.0011165	-7.84	0.000	-.0113959	-.0061156
x4	.0153965	.001991	7.73	0.000	.0106885	.0201046
x6	-.0071881	.0008978	-8.01	0.000	-.0093111	-.0050651
x8	-.0019572	.0017866	-1.10	0.310	-.0061817	.0022674
x10	.0042869	.0019979	2.15	0.069	-.0004375	.0090113
x12	.0008778	.0010178	0.86	0.417	-.0015288	.0032845
x14	2.98e-06	4.30e-07	6.93	0.000	1.96e-06	3.99e-06
x15	.0124617	.0012699	9.81	0.000	.009459	.0154645
x16	-.013834	.001786	-7.75	0.000	-.0180573	-.0096108
x17	.0066942	.0008973	7.46	0.000	.0045725	.0088159
x18	.0086356	.002131	4.05	0.005	.0035965	.0136747
x19	-.0052125	.0020338	-2.56	0.037	-.0100216	-.0004033
x20	-.0006865	.000772	-0.89	0.403	-.0025119	.0011388
x21	-2.50e-06	5.59e-07	-4.46	0.003	-3.82e-06	-1.17e-06
_cons	.0986563	.0636765	1.55	0.165	-.0519148	.2492274

. test x2 x4 x6 x15 x16 x17

- ( 1) x2 = 0
- ( 2) x4 = 0
- ( 3) x6 = 0
- ( 4) x15 = 0
- ( 5) x16 = 0
- ( 6) x17 = 0

F( 6, 7) = 126.12  
 Prob > F = 0.0000

. test x2 x4 x6

- ( 1) x2 = 0
- ( 2) x4 = 0
- ( 3) x6 = 0

F( 3, 7) = 28.27  
 Prob > F = 0.0003

. test x15 x16 x17

- ( 1) x15 = 0
- ( 2) x16 = 0
- ( 3) x17 = 0

F( 3, 7) = 51.10  
 Prob > F = 0.0000

. test x8 x10 x12 x18 x19 x20

- ( 1) x8 = 0
- ( 2) x10 = 0
- ( 3) x12 = 0
- ( 4) x18 = 0
- ( 5) x19 = 0
- ( 6) x20 = 0

F( 6, 7) = 39.64  
 Prob > F = 0.0000

. test x8 x10 x12

- ( 1) x8 = 0
- ( 2) x10 = 0
- ( 3) x12 = 0

F( 3, 7) = 36.89  
 Prob > F = 0.0001

. test x18 x19 x20

- ( 1) x18 = 0
- ( 2) x19 = 0
- ( 3) x20 = 0

F( 3, 7) = 9.06  
 Prob > F = 0.0083

. test x14 x21

- ( 1) x14 = 0
- ( 2) x21 = 0

F( 2, 7) = 89.68  
 Prob > F = 0.0000

```

. predict u17,r
.
. predict y17hat,xb
.
. reg lnb x2 x4 x6 x8 x10 x12 x14 x15 x16 x17 x18 x19 x20 x21 l.u17,robust cluste
> r(PD)

```

Linear regression

Number of obs =	2464
F( 6, 7) =	.
Prob > F =	.
R-squared =	0.5185
Root MSE =	.20418

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	-.0089061	.0011534	-7.72	0.000	-.0116334	-.0061787
x4	.0154271	.0019754	7.81	0.000	.010756	.0200981
x6	-.0070481	.0008426	-8.36	0.000	-.0090406	-.0050556
x8	-.0005667	.0018253	-0.31	0.765	-.0048828	.0037494
x10	.0026879	.0015957	1.68	0.136	-.0010854	.0064612
x12	.001219	.0008668	1.41	0.202	-.0008305	.0032685
x14	2.98e-06	4.11e-07	7.26	0.000	2.01e-06	3.95e-06
x15	.0131037	.0013283	9.86	0.000	.0099627	.0162447
x16	-.0142319	.0018084	-7.87	0.000	-.0185081	-.0099557
x17	.0064582	.000818	7.90	0.000	.004524	.0083923
x18	.0063231	.0019289	3.28	0.014	.001762	.0108843
x19	-.002544	.0016343	-1.56	0.164	-.0064086	.0013206
x20	-.0014222	.0006367	-2.23	0.061	-.0029277	.0000834
x21	-2.51e-06	5.19e-07	-4.84	0.002	-3.74e-06	-1.28e-06
u17						
l1.	.1772363	.0428438	4.14	0.004	.0759268	.2785458
_cons	.1015142	.0520816	1.95	0.092	-.0216392	.2246676

```

. gen y172=y17hat*y17hat
.
. gen y173=y172*y17hat
.
. reg lnb x2 x4 x6 x8 x10 x12 x14 x15 x16 x17 x18 x19 x20 x21 y172 y173, robust c
> luster(PD)

```

Linear regression

Number of obs =	2472
F( 6, 7) =	.
Prob > F =	.
R-squared =	0.5178
Root MSE =	.20407

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	-.0075337	.00125	-6.03	0.001	-.0104895	-.0045778
x4	.0134873	.0022732	5.93	0.001	.008112	.0188626
x6	-.0066372	.0010948	-6.06	0.001	-.009226	-.0040483
x8	-.0018175	.0015855	-1.15	0.289	-.0055665	.0019315
x10	.0057888	.0016652	3.48	0.010	.0018512	.0097263
x12	-.0002909	.000821	-0.35	0.734	-.0022323	.0016506
x14	2.61e-06	4.87e-07	5.36	0.001	1.46e-06	3.76e-06
x15	.0116285	.0016072	7.24	0.000	.0078281	.0154288
x16	-.0120629	.0019899	-6.06	0.001	-.0167682	-.0073576
x17	.0062861	.001136	5.53	0.001	.0036	.0089723
x18	.00608	.0020184	3.01	0.020	.0013073	.0108527
x19	-.005531	.0018654	-2.96	0.021	-.009942	-.0011199
x20	.0008004	.0005914	1.35	0.218	-.000598	.0021987
x21	-2.11e-06	5.99e-07	-3.53	0.010	-3.53e-06	-6.97e-07
y172	.535849	.1097637	4.88	0.002	.2762992	.7953989
y173	-.3659088	.49756	-0.74	0.486	-1.542451	.8106338
_cons	.1037757	.0627467	1.65	0.142	-.0445967	.2521482

```

. test y172 y173
( 1) y172 = 0
( 2) y173 = 0

F( 2, 7) = 17.81
Prob > F = 0.0018

```

. \*18 test all actual variables and diff. variables reservoir level

. reg lnb x2 x4 x6 x15 x16 x17,robust cluster(PD)

Linear regression Number of obs = 2472  
F( 6, 7) = 80.02  
Prob > F = 0.0000  
R-squared = 0.4536  
Root MSE = .2168

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	-.0026183	.0004363	-6.00	0.001	-.0036499	-.0015867
x4	.0017054	.0004282	3.98	0.005	.0006929	.002718
x6	.0010124	.0002597	3.90	0.006	.0003983	.0016265
x15	.006396	.0004797	13.33	0.000	.0052617	.0075303
x16	.0001854	.0002236	0.83	0.434	-.0003434	.0007143
x17	-.0013876	.0002683	-5.17	0.001	-.0020222	-.0007531
_cons	.1016835	.0601779	1.69	0.135	-.0406147	.2439817

. test x2 x4 x6

( 1) x2 = 0  
( 2) x4 = 0  
( 3) x6 = 0

F( 3, 7) = 23.04  
Prob > F = 0.0005

. test x15 x16 x17

( 1) x15 = 0  
( 2) x16 = 0  
( 3) x17 = 0

F( 3, 7) = 61.82  
Prob > F = 0.0000

. predict u18,r

. predict y18hat,xb

. reg lnb x2 x4 x6 x15 x16 x17 l.u18,robust cluster(PD)

Linear regression Number of obs = 2464  
F( 6, 7) = .  
Prob > F = .  
R-squared = 0.4750  
Root MSE = .21285

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	-.0024063	.000376	-6.40	0.000	-.0032955	-.0015172
x4	.0015007	.0003786	3.96	0.005	.0006054	.002396
x6	.0009763	.0002207	4.42	0.003	.0004544	.0014982
x15	.006655	.0004412	15.08	0.000	.0056118	.0076982
x16	.0000906	.000178	0.51	0.626	-.0003303	.0005115
x17	-.0014806	.0002543	-5.82	0.001	-.0020818	-.0008794
u18						
l1.	.1990155	.0390178	5.10	0.001	.1067531	.291278
_cons	.1044726	.0476556	2.19	0.064	-.008215	.2171602



```

. gen y182=y18hat*y18hat
.
. gen y183=y182*y18hat
.
. reg lnb x2 x4 x6 x15 x16 x17 y182 y183, robust cluster(PD)
Linear regression                               Number of obs =    2472
                                                F( 6,      7) =      .
                                                Prob > F      =
                                                R-squared    =    0.4706
                                                Root MSE    =    .21349

```

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	-.0025659	.0005402	-4.75	0.002	-.0038434	-.0012885
x4	.0016546	.0004381	3.78	0.007	.0006187	.0026905
x6	.0008621	.0002858	3.02	0.019	.0001864	.0015378
x15	.0065145	.0009676	6.73	0.000	.0042266	.0088025
x16	-.0000352	.0001998	-0.18	0.865	-.0005077	.0004373
x17	-.0009714	.0002581	-3.76	0.007	-.0015818	-.000361
y182	.6845781	.1286799	5.32	0.001	.3802984	.9888578
y183	-.1216124	.6062648	-0.20	0.847	-1.555201	1.311976
_cons	.1052387	.0595095	1.77	0.120	-.0354788	.2459562

```

. test y182 y183
( 1) y182 = 0
( 2) y183 = 0
      F( 2,      7) =    16.93
      Prob > F =    0.0021

```

. \*19 test all actual variables and diff. variables inflow

. reg ln b x8 x10 x12 x18 x19 x20,robust cluster(PD)

Linear regression Number of obs = 2472  
F( 6, 7) = 75.37  
Prob > F = 0.0000  
R-squared = 0.1718  
Root MSE = .26691

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x8	-.0242453	.0093534	-2.59	0.036	-.0463625	-.0021281
x10	.0274322	.0084729	3.24	0.014	.007397	.0474674
x12	-.0097012	.0035856	-2.71	0.030	-.0181797	-.0012227
x18	.0475456	.0094813	5.01	0.002	.025126	.0699652
x19	-.0339847	.0082513	-4.12	0.004	-.0534959	-.0144735
x20	.0130513	.0033001	3.95	0.005	.0052477	.0208549
_cons	.0594513	.047509	1.25	0.251	-.0528896	.1717923

. test x8 x10 x12

- ( 1) x8 = 0
- ( 2) x10 = 0
- ( 3) x12 = 0

F( 3, 7) = 34.08  
Prob > F = 0.0002

. test x18 x19 x20

- ( 1) x18 = 0
- ( 2) x19 = 0
- ( 3) x20 = 0

F( 3, 7) = 111.98  
Prob > F = 0.0000

. predict u19,r

. predict y19hat,xb

. reg ln b x8 x10 x12 x18 x19 x20 l.u19,robust cluster(PD)

Linear regression Number of obs = 2464  
F( 6, 7) = .  
Prob > F = .  
R-squared = 0.1734  
Root MSE = .26709

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x8	-.0236744	.0087233	-2.71	0.030	-.0443018	-.003047
x10	.0268751	.0078715	3.41	0.011	.008262	.0454883
x12	-.0095669	.0033714	-2.84	0.025	-.017539	-.0015949
x18	.0470766	.0088551	5.32	0.001	.0261377	.0680156
x19	-.0332134	.0075457	-4.40	0.003	-.0510561	-.0153708
x20	.0128841	.0030779	4.19	0.004	.0056061	.0201622
u19						
l1.	.0464186	.0232153	2.00	0.086	-.0084769	.101314
_cons	.0596486	.0453699	1.31	0.230	-.0476342	.1669314

```

. gen y192=y19hat*y19hat
.
. gen y193=y192*y19hat
.
. reg lnb x8 x10 x12 x18 x19 x20 y192 y193, robust cluster(PD)
Linear regression                               Number of obs =    2472
                                                F( 6,          7) =    .
                                                Prob > F       =    .
                                                R-squared     =    0.2108
                                                Root MSE     =    .26066

```

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x8	-.0314375	.0095652	-3.29	0.013	-.0540557	-.0088193
x10	.0359838	.0086778	4.15	0.004	.0154642	.0565034
x12	-.0124106	.0036357	-3.41	0.011	-.0210076	-.0038136
x18	.0601119	.0099407	6.05	0.001	.0366058	.083618
x19	-.0442386	.0085188	-5.19	0.001	-.0643825	-.0240948
x20	.0190933	.0034212	5.58	0.001	.0110034	.0271831
y192	.3728771	.3617583	1.03	0.337	-.4825454	1.2283
y193	-2.210985	.3315849	-6.67	0.000	-2.995058	-1.426911
_cons	.0528807	.0474846	1.11	0.302	-.0594024	.1651639

```

. test y192 y193
( 1) y192 = 0
( 2) y193 = 0
      F( 2,          7) =    31.84
      Prob > F =    0.0003

```

. \*20 test all actual variables and diff. variables snow

. reg lnb x14 x21,robust cluster(PD)

Linear regression

Number of obs =	2472
F( 2, 7) =	157.95
Prob > F =	0.0000
R-squared =	0.1164
Root MSE =	.27547

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x14	-1.50e-07	1.23e-07	-1.22	0.263	-4.42e-07	1.42e-07
x21	1.96e-06	1.78e-07	11.04	0.000	1.54e-06	2.38e-06
_cons	.0716266	.0342029	2.09	0.075	-.0092503	.1525036

. predict u20,r

. predict y20hat,xb

. reg lnb x14 x21 l.u20,robust cluster(PD)

Linear regression

Number of obs =	2464
F( 3, 7) =	272.31
Prob > F =	0.0000
R-squared =	0.1183
Root MSE =	.27564

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x14	-1.46e-07	1.20e-07	-1.22	0.264	-4.30e-07	1.38e-07
x21	1.96e-06	1.71e-07	11.50	0.000	1.56e-06	2.36e-06
u20						
l1.	.0468256	.0292994	1.60	0.154	-.0224565	.1161077
_cons	.0710398	.0325285	2.18	0.065	-.0058778	.1479574

. gen y202=y20hat\*y20hat

. gen y203=y202\*y20hat

. reg lnb x14 x21 y202 y203, robust cluster(PD)

Linear regression

Number of obs =	2472
F( 4, 7) =	195.03
Prob > F =	0.0000
R-squared =	0.1697
Root MSE =	.26715

(Std. Err. adjusted for 8 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x14	-9.43e-08	1.20e-07	-0.79	0.458	-3.78e-07	1.90e-07
x21	3.06e-06	2.81e-07	10.90	0.000	2.40e-06	3.73e-06
y202	-.6843288	.794527	-0.86	0.418	-2.563087	1.194429
y203	-5.165943	2.235692	-2.31	0.054	-10.45252	.1206286
_cons	.0793833	.0346522	2.29	0.056	-.0025561	.1613228

. test y202 y203

( 1) y202 = 0

( 2) y203 = 0

F( 2, 7) = 45.67  
 Prob > F = 0.0001

## Year

```
. xtfisher ln b, lags(5)
```

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

```
chi2(6) = 227.4966
Prob > chi2 = 0.0000
```

```
. xtfisher x1, lags(5)
```

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

```
chi2(6) = 285.7111
Prob > chi2 = 0.0000
```

```
. xtfisher x2, lags(5)
```

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

```
chi2(6) = 317.6213
Prob > chi2 = 0.0000
```

```
. xtfisher x3, lags(5)
```

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

```
chi2(6) = 298.5616
Prob > chi2 = 0.0000
```

```
. xtfisher x4, lags(5)
```

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

```
chi2(6) = 308.8823
Prob > chi2 = 0.0000
```

```
. xtfisher x5, lags(5)
```

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

```
chi2(6) = 275.5370
Prob > chi2 = 0.0000
```

```
. xtfisher x6, lags(5)
```

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

```
chi2(6) = 282.2660
Prob > chi2 = 0.0000
```

. xtfisher x7, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(6) = 294.1965  
Prob > chi2 = 0.0000

. xtfisher x8, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(6) = 279.0134  
Prob > chi2 = 0.0000

. xtfisher x9, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(6) = 279.6077  
Prob > chi2 = 0.0000

. xtfisher x10, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(6) = 262.2707  
Prob > chi2 = 0.0000

. xtfisher x11, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(6) = 252.1105  
Prob > chi2 = 0.0000

. xtfisher x12, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(6) = 245.5669  
Prob > chi2 = 0.0000

. xtfisher x13, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(6) = 361.1272  
Prob > chi2 = 0.0000

. xtfisher x14, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(6) = 373.5609  
Prob > chi2 = 0.0000

. xtfisher x15, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(6) = 260.8225  
Prob > chi2 = 0.0000

. xtfisher x16, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(6) = 239.3598  
Prob > chi2 = 0.0000

. xtfisher x17, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(6) = 213.7644  
Prob > chi2 = 0.0000

. xtfisher x18, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(6) = 164.5724  
Prob > chi2 = 0.0000

. xtfisher x19, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(6) = 171.8518  
Prob > chi2 = 0.0000

. xtfisher x20, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(6) = 216.1269  
Prob > chi2 = 0.0000

. xtfisher x21, lags(5)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (5 lags)

Ho: unit root

chi2(6) = 190.4616  
Prob > chi2 = 0.0000

. \*1 test actual variables

. reg lnb x2 x4 x6 x8 x10 x12 x14,robust cluster(PD)

Linear regression Number of obs = 1533  
F( 1, 2) = .  
Prob > F = .  
R-squared = 0.1311  
Root MSE = .28459

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	.0004493	.0002595	1.73	0.226	-.0006673	.0015659
x4	.0002931	.0002434	1.20	0.352	-.0007541	.0013402
x6	-.0009579	.0002558	-3.75	0.064	-.0020583	.0001425
x8	.0091781	.0023076	3.98	0.058	-.0007507	.0191069
x10	-.002922	.0010823	-2.70	0.114	-.0075789	.0017349
x12	.002029	.0005426	3.74	0.065	-.0003054	.0043635
x14	2.05e-07	4.57e-08	4.49	0.046	8.46e-09	4.01e-07
_cons	-.0960715	.0811422	-1.18	0.358	-.4451982	.2530552

. test x2 x4 x6

( 1) x2 = 0  
( 2) x4 = 0  
( 3) x6 = 0  
Constraint 2 dropped  
F( 2, 2) = 10.37  
Prob > F = 0.0879

. test x8 x10 x12

( 1) x8 = 0  
( 2) x10 = 0  
( 3) x12 = 0  
Constraint 3 dropped  
F( 2, 2) = 31.16  
Prob > F = 0.0311

. predict u,r

. predict yhat,xb

. reg lnb x2 x4 x6 x8 x10 x12 x14 l.u,robust cluster(PD)

Linear regression Number of obs = 1530  
F( 1, 2) = .  
Prob > F = .  
R-squared = 0.1411  
Root MSE = .28329

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	.0003132	.0002771	1.13	0.376	-.0008789	.0015053
x4	.0003754	.0002618	1.43	0.288	-.0007512	.0015021
x6	-.0009123	.0002254	-4.05	0.056	-.0018821	.0000575
x8	.0090508	.0023439	3.86	0.061	-.0010341	.0191357
x10	-.0030195	.0011458	-2.64	0.119	-.0079493	.0019104
x12	.0021124	.0005869	3.60	0.069	-.000413	.0046378
x14	1.81e-07	3.59e-08	5.03	0.037	2.62e-08	3.35e-07
u						
l1.	-.112679	.0212398	-5.31	0.034	-.2040665	-.0212915
_cons	-.0837237	.0817637	-1.02	0.414	-.4355246	.2680772



```

. gen y2=yhat*yhat
.
. gen y3=y2*yhat
.
. reg lnb x2 x4 x6 x8 x10 x12 x14 y2 y3, robust cluster(PD)
Linear regression                               Number of obs = 1533
                                                F( 1, 2) = .
                                                Prob > F = .
                                                R-squared = 0.1447
                                                Root MSE = .28254
                                                (Std. Err. adjusted for 3 clusters in PD)

```

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	.0005704	.0002563	2.23	0.156	-.0005324	.0016731
x4	.0002756	.0001897	1.45	0.283	-.0005407	.0010918
x6	-.0011554	.0002581	-4.48	0.046	-.002266	-.0000447
x8	.0126313	.0037648	3.36	0.079	-.0035673	.0288299
x10	-.0040721	.0014715	-2.77	0.110	-.0104036	.0022594
x12	.0025981	.0006083	4.27	0.051	-.0000193	.0052156
x14	2.44e-07	5.30e-08	4.60	0.044	1.56e-08	4.72e-07
y2	-.860957	1.960895	-0.44	0.703	-9.298006	7.576092
y3	-1.043995	1.984817	-0.53	0.651	-9.583975	7.495985
_cons	-.1038163	.0905605	-1.15	0.370	-.4934668	.2858341

```

. test y2 y3
( 1) y2 = 0
( 2) y3 = 0
      F( 2, 2) = 11.21
      Prob > F = 0.0819

```

. \*2 test actual variables reservoir level

. reg lnb x2 x4 x6, robust cluster(PD)

Linear regression Number of obs = 1533  
F( 1, 2) = .  
Prob > F = .  
R-squared = 0.0297  
Root MSE = .30033

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	-.0002158	.0002889	-0.75	0.533	-.0014587	.0010271
x4	.0002125	.000257	0.83	0.495	-.0008934	.0013184
x6	.0002707	.0000551	4.91	0.039	.0000335	.0005079
_cons	-.0796321	.0668727	-1.19	0.356	-.3673619	.2080977

. predict u2,r

. predict y2hat,xb

. reg lnb x2 x4 x6 l.u2, robust cluster(PD)

Linear regression Number of obs = 1530  
F( 1, 2) = .  
Prob > F = .  
R-squared = 0.0465  
Root MSE = .2981

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	-.0004734	.0003252	-1.46	0.283	-.0018728	.000926
x4	.0003991	.0002914	1.37	0.304	-.0008547	.0016529
x6	.0003235	.0000548	5.91	0.027	.0000879	.0005591
u2						
L1.	-.1375666	.0120667	-11.40	0.008	-.1894855	-.0856477
_cons	-.0675868	.0664566	-1.02	0.416	-.3535267	.218353

. gen y22=y2hat\*y2hat

. gen y23=y22\*y2hat

. reg lnb x2 x4 x6 y22 y23, robust cluster(PD)

Linear regression Number of obs = 1533  
F( 1, 2) = .  
Prob > F = .  
R-squared = 0.0298  
Root MSE = .30051

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	-.000189	.0004502	-0.42	0.715	-.0021263	.0017482
x4	.0001925	.0003952	0.49	0.674	-.0015079	.0018929
x6	.0002545	.0001263	2.02	0.181	-.0002889	.0007979
y22	.6316702	13.11283	0.05	0.966	-55.7883	57.05164
y23	3.104251	73.04759	0.04	0.970	-311.1941	317.4026
_cons	-.0792731	.1119705	-0.71	0.552	-.5610431	.4024968

. test y22 y23

( 1) y22 = 0

( 2) y23 = 0

F( 2, 2) = 0.02  
Prob > F = 0.9804

. \*3 test actual variables inflow

. reg lnb x8 x10 x12,robust cluster(PD)

Linear regression

Number of obs =	1533
F( 1, 2) =	.
Prob > F =	.
R-squared =	0.1043
Root MSE =	.28856

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x8	.0076947	.001669	4.61	0.044	.0005137	.0148757
x10	-.0026403	.0006534	-4.04	0.056	-.0054515	.0001709
x12	.0012783	.0004671	2.74	0.112	-.0007313	.0032879
_cons	-.0931585	.0406706	-2.29	0.149	-.2681502	.0818332

. predict u3, r

. predict y3hat,xb

. reg lnb x8 x10 x12 1.u3,robust cluster(PD)

Linear regression

Number of obs =	1530
F( 1, 2) =	.
Prob > F =	.
R-squared =	0.1196
Root MSE =	.28645

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x8	.007365	.0017019	4.33	0.049	.0000424	.0146875
x10	-.002515	.0006659	-3.78	0.063	-.00538	.00035
x12	.0012394	.0005218	2.38	0.141	-.0010056	.0034845
u3	-.1316842	.0276267	-4.77	0.041	-.2505524	-.0128159
_cons	-.0898604	.0447282	-2.01	0.182	-.2823104	.1025895

. gen y32=y3hat\*y3hat

. gen y33=y32\*y3hat

. reg lnb x8 x10 x12 y32 y33, robust cluster(PD)

Linear regression

Number of obs =	1533
F( 1, 2) =	.
Prob > F =	.
R-squared =	0.1200
Root MSE =	.2862

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x8	.0116713	.0024966	4.67	0.043	.0009292	.0224133
x10	-.0037996	.00085	-4.47	0.047	-.0074568	-.0001424
x12	.0015242	.0006872	2.22	0.157	-.0014327	.0044812
y32	-4.190618	2.637345	-1.59	0.253	-15.5382	7.156963
y33	4.303015	4.053527	1.06	0.400	-13.1379	21.74394
_cons	-.1034649	.0635836	-1.63	0.245	-.3770432	.1701134

. test y32 y33

( 1) y32 = 0  
( 2) y33 = 0

F( 2, 2) = 4.51  
Prob > F = 0.1814

. \*4 test actual variables snow

. reg lnb x14,robust cluster(PD)

Linear regression

Number of obs = 1533  
 F( 1, 2) = 51.32  
 Prob > F = 0.0189  
 R-squared = 0.0168  
 Root MSE = .30213

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x14	1.77e-07	2.47e-08	7.16	0.019	7.06e-08	2.83e-07
_cons	-.0355338	.0123366	-2.88	0.102	-.0886139	.0175464

. predict u4,r

. predict y4hat,xb

. reg lnb x14 l.u4,robust cluster(PD)

Linear regression

Number of obs = 1530  
 F( 1, 2) = .  
 Prob > F = .  
 R-squared = 0.0260  
 Root MSE = .30109

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x14	1.42e-07	1.89e-08	7.51	0.017	6.04e-08	2.23e-07
u4	-.0999829	.009194	-10.87	0.008	-.1395414	-.0604245
_cons	-.0287021	.0114563	-2.51	0.129	-.0779948	.0205905

. gen y42=y4hat\*y4hat

. gen y43=y42\*y4hat

. reg lnb x14 y42 y43, robust cluster(PD)

Linear regression

Number of obs = 1533  
 F( 1, 2) = .  
 Prob > F = .  
 R-squared = 0.0400  
 Root MSE = .29874

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x14	-2.17e-08	1.73e-07	-0.13	0.912	-7.67e-07	7.24e-07
y42	38.36147	28.45902	1.35	0.310	-84.08782	160.8108
y43	-122.3204	245.3345	-0.50	0.668	-1177.91	933.2689
_cons	-.0484704	.0396964	-1.22	0.346	-.2192704	.1223295

. test y42 y43

( 1) y42 = 0  
 ( 2) y43 = 0

F( 2, 2) = 4.30  
 Prob > F = 0.1888

. \*5 Test all seasonal variables

. reg lnb x1 x3 x5 x7 x9 x11 x13,robust cluster(PD)

Linear regression

Number of obs =	1533
F( 1, 2) =	.
Prob > F =	.
R-squared =	0.0664
Root MSE =	.29499

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	-.0025076	.000444	-5.65	0.030	-.004418	-.0005973
x3	.0055275	.0009557	5.78	0.029	.0014153	.0096396
x5	-.0033841	.0005821	-5.81	0.028	-.0058887	-.0008795
x7	-.0041645	.0012128	-3.43	0.075	-.0093826	.0010536
x9	.0094284	.0020812	4.53	0.045	.0004739	.0183829
x11	-.0022971	.0004127	-5.57	0.031	-.0040726	-.0005216
x13	1.15e-06	1.72e-07	6.72	0.021	4.15e-07	1.89e-06
_cons	-.0120814	.0106786	-1.13	0.375	-.0580278	.0338649

. test x1 x3 x5

( 1) x1 = 0  
 ( 2) x3 = 0  
 ( 3) x5 = 0  
 Constraint 3 dropped  
 F( 2, 2) = 17.56  
 Prob > F = 0.0539

. test x7 x9 x11

( 1) x7 = 0  
 ( 2) x9 = 0  
 ( 3) x11 = 0  
 Constraint 1 dropped  
 F( 2, 2) = 19.38  
 Prob > F = 0.0491

. predict u5,r

. predict y5hat,xb

. reg lnb x1 x3 x5 x7 x9 x11 x13 l.u5,robust cluster(PD)

Linear regression

Number of obs =	1530
F( 1, 2) =	.
Prob > F =	.
R-squared =	0.1128
Root MSE =	.28793

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	-.0028502	.0006076	-4.69	0.043	-.0054647	-.0002357
x3	.0063738	.0012966	4.92	0.039	.0007949	.0119527
x5	-.0039399	.0007765	-5.07	0.037	-.007281	-.0005988
x7	-.0042918	.0011291	-3.80	0.063	-.0091499	.0005663
x9	.0099225	.002205	4.50	0.046	.0004352	.0194097
x11	-.0022766	.0004022	-5.66	0.030	-.0040069	-.0005462
x13	1.32e-06	2.31e-07	5.72	0.029	3.27e-07	2.31e-06
u5						
l1.	-.2243479	.0269973	-8.31	0.014	-.340508	-.1081877
_cons	-.0090809	.0116357	-0.78	0.517	-.0591451	.0409834

```

. gen y52=y5hat*y5hat
.
. gen y53=y52*y5hat
.
. reg lnb x1 x3 x5 x7 x9 x11 x13 y52 y53, robust cluster(PD)
Linear regression                               Number of obs =   1533
                                                F( 1, 2) = .
                                                Prob > F = .
                                                R-squared = 0.0825
                                                Root MSE = 0.29262

```

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	-.0062099	.0003245	-19.14	0.003	-.007606	-.0048138
x3	.012469	.0004897	25.46	0.002	.0103622	.0145759
x5	-.006836	.0002645	-25.84	0.001	-.0079742	-.0056978
x7	-.0112121	.0023384	-4.79	0.041	-.0212735	-.0011506
x9	.0181972	.0032104	5.67	0.030	.004384	.0320105
x11	-.0044138	.0009537	-4.63	0.044	-.0085171	-.0003105
x13	2.59e-06	7.94e-08	32.61	0.001	2.25e-06	2.93e-06
y52	-.1640516	.7048005	-0.23	0.838	-3.196564	2.86846
y53	-27.52051	6.245712	-4.41	0.048	-54.39365	-.6473827
_cons	-.0152893	.0076488	-2.00	0.184	-.0481996	.017621

```

. test y52 y53
( 1) y52 = 0
( 2) y53 = 0
      F( 2, 2) = 24.99
      Prob > F = 0.0385

```

. \*6 Test all seasonal variables reservoir level

. reg lnb x1 x3 x5,robust cluster(PD)

Linear regression

Number of obs =	1533
F( 1, 2) =	.
Prob > F =	.
R-squared =	0.0359
Root MSE =	.29937

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	-.001536	.0003581	-4.29	0.050	-.0030768	4.80e-06
x3	.0009042	.0002478	3.65	0.068	-.0001621	.0019704
x5	.000743	.0001345	5.52	0.031	.0001641	.0013219
_cons	.0022829	.0019059	1.20	0.354	-.0059176	.0104834

. predict u6,r

. predict y6hat,xb

. reg lnb x1 x3 x5 l.u6,robust cluster(PD)

Linear regression

Number of obs =	1530
F( 1, 2) =	.
Prob > F =	.
R-squared =	0.0656
Root MSE =	.29509

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	-.0016643	.0004313	-3.86	0.061	-.0035201	.0001916
x3	.0010513	.0003204	3.28	0.082	-.0003275	.00243
x5	.0007303	.0001416	5.16	0.036	.0001212	.0013394
u6						
L1.	-.1768067	.0181211	-9.76	0.010	-.2547756	-.0988377
_cons	.0056889	.0044253	1.29	0.327	-.0133515	.0247293

. gen y62=y6hat\*y6hat

. gen y63=y62\*y6hat

. reg lnb x1 x3 x5 y62 y63, robust cluster(PD)

Linear regression

Number of obs =	1533
F( 1, 2) =	.
Prob > F =	.
R-squared =	0.0485
Root MSE =	.29761

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	-.0025676	.000405	-6.34	0.024	-.0043102	-.000825
x3	.0016598	.0002593	6.40	0.024	.000544	.0027756
x5	.0010655	.0001803	5.91	0.027	.0002898	.0018412
y62	11.22132	1.610809	6.97	0.020	4.290571	18.15207
y63	-83.84504	16.3182	-5.14	0.036	-154.0566	-13.63351
_cons	.0018804	.0003505	5.36	0.033	.0003722	.0033885

. test y62 y63

( 1) y62 = 0  
( 2) y63 = 0

F( 2, 2) = 64.36  
Prob > F = 0.0153

. \*7 Test all seasonal variables inflow

. reg lnb x7 x9 x11,robust cluster(PD)

Linear regression

Number of obs = 1533  
 F( 1, 2) = .  
 Prob > F = .  
 R-squared = 0.0523  
 Root MSE = .29681

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x7	-.0114847	.0043626	-2.63	0.119	-.0302556	.0072862
x9	.0153904	.0049178	3.13	0.089	-.0057691	.0365499
x11	-.0058835	.0019435	-3.03	0.094	-.0142456	.0024786
_cons	-.0270992	.0155386	-1.74	0.223	-.0939564	.0397581

. predict u7,r

. predict y7hat,xb

. reg lnb x7 x9 x11 l.u7,robust cluster(PD)

Linear regression

Number of obs = 1530  
 F( 1, 2) = .  
 Prob > F = .  
 R-squared = 0.0896  
 Root MSE = .29129

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x7	-.0122539	.0050328	-2.43	0.135	-.0339085	.0094006
x9	.0163533	.0057466	2.85	0.104	-.0083722	.0410787
x11	-.0063128	.0023532	-2.68	0.115	-.0164378	.0038121
u7	-.1988379	.0250131	-7.95	0.015	-.3064605	-.0912154
_cons	-.0266349	.0188668	-1.41	0.294	-.1078123	.0545425

. gen y72=y7hat\*y7hat

. gen y73=y72\*y7hat

. reg lnb x7 x9 x11 y72 y73, robust cluster(PD)

Linear regression

Number of obs = 1533  
 F( 1, 2) = .  
 Prob > F = .  
 R-squared = 0.0730  
 Root MSE = .29375

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x7	-.0173703	.0031133	-5.58	0.031	-.0307658	-.0039748
x9	.0245417	.0043638	5.62	0.030	.0057659	.0433174
x11	-.0089637	.0016279	-5.51	0.031	-.015968	-.0019594
y72	-10.78616	5.816983	-1.85	0.205	-35.81461	14.2423
y73	18.32997	15.86188	1.16	0.367	-49.91817	86.57811
_cons	-.025372	.0117381	-2.16	0.163	-.0758769	.0251329

. test y72 y73

( 1) y72 = 0  
 ( 2) y73 = 0

F( 2, 2) = 92.03  
 Prob > F = 0.0107



. \*8 Test all seasonal variables snow

. reg lnb x13,robust cluster(PD)

Linear regression

Number of obs = 1533  
 F( 1, 2) = 0.09  
 Prob > F = 0.7966  
 R-squared = 0.0000  
 Root MSE = .30469

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x13	<b>-6.09e-09</b>	<b>2.07e-08</b>	<b>-0.29</b>	<b>0.797</b>	<b>-9.53e-08</b>	<b>8.31e-08</b>
_cons	<b>-.000649</b>	<b>.0023188</b>	<b>-0.28</b>	<b>0.806</b>	<b>-.0106261</b>	<b>.0093282</b>

. predict u8,r

. predict y8hat,xb

. reg lnb x13 l.u8,robust cluster(PD)

Linear regression

Number of obs = 1530  
 F( 1, 2) = .  
 Prob > F = .  
 R-squared = 0.0159  
 Root MSE = .30265

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x13	<b>-3.09e-08</b>	<b>2.72e-08</b>	<b>-1.14</b>	<b>0.373</b>	<b>-1.48e-07</b>	<b>8.59e-08</b>
u8	<b>-.1271444</b>	<b>.0120937</b>	<b>-10.51</b>	<b>0.009</b>	<b>-.1791792</b>	<b>-.0751095</b>
_cons	<b>.0041613</b>	<b>.0012198</b>	<b>3.41</b>	<b>0.076</b>	<b>-.0010872</b>	<b>.0094099</b>

. gen y82=y8hat\*y8hat

. gen y83=y82\*y8hat

. reg lnb x13 y82 y83, robust cluster(PD)

Linear regression

Number of obs = 1533  
 F( 1, 2) = .  
 Prob > F = .  
 R-squared = 0.0048  
 Root MSE = .30417

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x13	<b>-5.87e-07</b>	<b>1.06e-07</b>	<b>-5.52</b>	<b>0.031</b>	<b>-1.04e-06</b>	<b>-1.30e-07</b>
y82	<b>26225.16</b>	<b>6342.436</b>	<b>4.13</b>	<b>0.054</b>	<b>-1064.137</b>	<b>53514.47</b>
y83	<b>1607335</b>	<b>735665.2</b>	<b>2.18</b>	<b>0.161</b>	<b>-1557977</b>	<b>4772647</b>
_cons	<b>.008442</b>	<b>.0054112</b>	<b>1.56</b>	<b>0.259</b>	<b>-.0148404</b>	<b>.0317243</b>

. test y82 y83

( 1) **y82 = 0**  
 ( 2) **y83 = 0**

F( 2, 2) = 24.25  
 Prob > F = 0.0396

. \*9 test all actual and season variables

. reg lnb x1 x2 x3 x4 x5 x6 x7 x8 x9 x10 x11 x12 x13 x14,robust cluster(PD)

Linear regression

Number of obs = 1533  
 F( 1, 2) = .  
 Prob > F = .  
 R-squared = 0.5100  
 Root MSE = .21419

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
x1	-.0101467	.0023577	-4.30	0.050	-.0202912 -2.22e-06
x2	.0029808	.0006432	4.63	0.044	.0002131 .0057484
x3	.0138616	.0031648	4.38	0.048	.0002444 .0274788
x4	-.0004938	.0001275	-3.87	0.061	-.0010423 -.0000546
x5	-.00067403	.0013672	-4.93	0.039	-.0126231 -.0008576
x6	.0002415	.0000989	2.44	0.135	-.0001841 .000667
x7	-.0041204	.0004632	-8.89	0.012	-.0061136 -.0021272
x8	.0043494	.0010497	4.14	0.054	-.0001673 .008866
x9	.0007926	.0008019	0.99	0.427	-.0026579 .0042431
x10	.0006806	.0000434	15.70	0.004	.0004941 .0008672
x11	.0005448	.0008049	0.68	0.568	-.0029185 .0040081
x12	.0008439	.0002347	3.60	0.069	-.0001659 .0018536
x13	1.75e-06	3.18e-07	5.50	0.031	3.82e-07 3.12e-06
x14	9.39e-07	2.61e-07	3.60	0.069	-1.84e-07 2.06e-06
_cons	-.010847	.0094492	-1.15	0.370	-.0515038 .0298098

. test x1 x2 x3 x4 x5 x6

( 1) x1 = 0  
 ( 2) x2 = 0  
 ( 3) x3 = 0  
 ( 4) x4 = 0  
 ( 5) x5 = 0  
 ( 6) x6 = 0  
 Constraint 1 dropped  
 Constraint 4 dropped  
 Constraint 5 dropped  
 Constraint 6 dropped  
 F( 2, 2) = 10.94  
 Prob > F = 0.0838

. test x1 x3 x5

( 1) x1 = 0  
 ( 2) x3 = 0  
 ( 3) x5 = 0  
 Constraint 1 dropped  
 F( 2, 2) = 46.36  
 Prob > F = 0.0211

. test x2 x3 x5

( 1) x2 = 0  
 ( 2) x3 = 0  
 ( 3) x5 = 0  
 Constraint 3 dropped  
 F( 2, 2) = 10.94  
 Prob > F = 0.0838

. test x7 x8 x9 x10 x11 x12

( 1) x7 = 0  
 ( 2) x8 = 0  
 ( 3) x9 = 0  
 ( 4) x10 = 0  
 ( 5) x11 = 0  
 ( 6) x12 = 0  
 Constraint 1 dropped  
 Constraint 3 dropped  
 Constraint 4 dropped  
 Constraint 6 dropped  
 F( 2, 2) = 20.62  
 Prob > F = 0.0462

. test x7 x9 x11

( 1) x7 = 0  
 ( 2) x9 = 0  
 ( 3) x11 = 0  
 Constraint 2 dropped  
 F( 2, 2) = 52.40  
 Prob > F = 0.0187

. test x8 x10 x12

( 1) x8 = 0  
 ( 2) x10 = 0  
 ( 3) x12 = 0  
 Constraint 2 dropped  
 F( 2, 2) = 8.76  
 Prob > F = 0.1025

. test x13 x14

( 1) x13 = 0  
 ( 2) x14 = 0  
 F( 2, 2) = 818.97  
 Prob > F = 0.0012

```

. predict u9,r
.
. predict y9hat,xb
.
. reg lnb x1 x2 x3 x4 x5 x6 x7 x8 x9 x10 x11 x12 x13 x14 l.u9,robust cluster(PD)

```

Linear regression

Number of obs =	1530
F( 1, 2) =	.
Prob > F =	.
R-squared =	0.5191
Root MSE =	.21246

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	-.0101424	.0024251	-4.18	0.053	-.0205768	.000292
x2	.0028861	.0005839	4.94	0.039	.000374	.0053982
x3	.0141262	.0034142	4.14	0.054	-.0005641	.0288165
x4	-.0004747	.0001194	-3.97	0.058	-.0009885	.0000391
x5	-.0070363	.0015408	-4.57	0.045	-.0136659	-.0004067
x6	.0003286	.000077	4.27	0.051	-2.78e-06	.00066
x7	-.0049654	.0006489	-7.65	0.017	-.0077573	-.0021734
x8	.0042758	.0010475	4.08	0.055	-.0002313	.0087828
x9	.0020252	.0007174	2.82	0.106	-.0010613	.0051118
x10	.0004657	.0001425	3.27	0.082	-.0001477	.001079
x11	.0000352	.0008122	0.04	0.969	-.0034596	.00353
x12	.0010514	.0003003	3.50	0.073	-.0002407	.0023435
x13	1.85e-06	3.71e-07	4.99	0.038	2.54e-07	3.45e-06
x14	9.00e-07	2.54e-07	3.55	0.071	-1.92e-07	1.99e-06
u9						
_l1.	-.1402437	.0287709	-4.87	0.040	-.2640349	-.0164526
_cons	-.0095109	.0102104	-0.93	0.450	-.0534426	.0344207

```

. gen y92=y9hat*y9hat
.
. gen y93=y92*y9hat
.
. reg lnb x1 x2 x3 x4 x5 x6 x7 x8 x9 x10 x11 x12 x13 x14 y92 y93, robust cluster(> PD)

```

Linear regression

Number of obs =	1533
F( 1, 2) =	.
Prob > F =	.
R-squared =	0.5141
Root MSE =	.21344

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	-.0111508	.0036977	-3.02	0.095	-.0270606	.0047589
x2	.0032021	.0009324	3.43	0.075	-.0008097	.0072139
x3	.0153217	.0051336	2.98	0.096	-.0067666	.03741
x4	-.0005	.0001277	-3.92	0.059	-.0010495	.0000495
x5	-.0075087	.0024818	-3.03	0.094	-.0181872	.0031697
x6	.00029	.0001504	1.93	0.194	-.0003574	.0009373
x7	-.0039973	.0004935	-8.10	0.015	-.0061208	-.0018738
x8	.0053698	.0022912	2.34	0.144	-.0044884	.0152281
x9	.0005231	.0010484	0.50	0.667	-.0039878	.005034
x10	.000532	.0001644	3.24	0.084	-.0001753	.0012393
x11	.00063	.000856	0.74	0.538	-.0030533	.0043132
x12	.0010159	.0003642	2.79	0.108	-.000551	.0025827
x13	1.96e-06	6.08e-07	3.22	0.084	-6.58e-07	4.58e-06
x14	1.03e-06	3.73e-07	2.76	0.110	-5.76e-07	2.64e-06
y92	-.0682359	.0701224	-0.97	0.433	-.3699484	.2334766
y93	-.4966731	.8338245	-0.60	0.612	-4.08433	3.090984
_cons	-.0129637	.0085377	-1.52	0.268	-.0496986	.0237711

```

. test y92 y93
( 1) y92 = 0
( 2) y93 = 0

F( 2, 2) = 1.16
Prob > F = 0.4632

```

. \*10 test all actual and season variables reservoir level

. reg lnb x1 x2 x3 x4 x5 x6,robust cluster(PD)

Linear regression

Number of obs =	1533
F( 1, 2) =	.
Prob > F =	.
R-squared =	0.4006
Root MSE =	.23629

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	-.0043868	.0009881	-4.44	0.047	-.0086383	-.0001352
x2	.0030588	.0006783	4.51	0.046	.0001401	.0059775
x3	.0011363	.000302	3.76	0.064	-.0001632	.0024359
x4	-.000171	.0000719	-2.38	0.141	-.0004803	.0001384
x5	.000048	.0000959	0.50	0.666	-.0003646	.0004607
x6	.0004964	.0000984	5.04	0.037	.000073	.0009197
_cons	.0066344	.0060823	1.09	0.389	-.0195356	.0328045

. test x1 x3 x5

( 1) x1 = 0  
 ( 2) x3 = 0  
 ( 3) x5 = 0  
 Constraint 2 dropped  
 F( 2, 2) = 15.66  
 Prob > F = 0.0600

. test x2 x4 x6

( 1) x2 = 0  
 ( 2) x4 = 0  
 ( 3) x6 = 0  
 Constraint 2 dropped  
 F( 2, 2) = 17.24  
 Prob > F = 0.0548

. predict u10,r

. predict y10hat,xb

. reg lnb x1 x2 x3 x4 x5 x6 l.u10,robust cluster(PD)

Linear regression

Number of obs =	1530
F( 1, 2) =	.
Prob > F =	.
R-squared =	0.4121
Root MSE =	.2343

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	-.004404	.0010132	-4.35	0.049	-.0087637	-.0000444
x2	.0029809	.0006393	4.66	0.043	.0002301	.0057316
x3	.0012975	.0003755	3.46	0.075	-.000318	.0029131
x4	-.0002422	.0000889	-2.73	0.112	-.0006246	.0001401
x5	-.0000459	.0000639	-0.72	0.547	-.0003208	.0002291
x6	.0006031	.0000941	6.41	0.024	.0001981	.0010081
u10						
l1.	-.138139	.0194134	-7.12	0.019	-.2216679	-.0546101
_cons	.0082556	.0076916	1.07	0.395	-.0248388	.04135

```

. gen y102=y10hat*y10hat
.
. gen y103=y102*y10hat
.
. reg lnb x1 x2 x3 x4 x5 x6 y102 y103, robust cluster(PD)
Linear regression                               Number of obs =   1533
                                                F( 1, 1530) =      .
                                                Prob > F       =
                                                R-squared     =  0.4021
                                                Root MSE     =  0.23614

```

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x1	-.0046344	.0017428	-2.66	0.117	-.0121332	.0028644
x2	.003187	.001114	2.86	0.104	-.001606	.00798
x3	.0012464	.0005845	2.13	0.167	-.0012686	.0037613
x4	-.0001713	.0000967	-1.77	0.218	-.0005872	.0002446
x5	-.0000574	.0000656	-0.87	0.474	-.0003397	.0002249
x6	.0006024	.000214	2.82	0.106	-.0003183	.001523
y102	.1212491	.0452917	2.68	0.116	-.0736252	.3161234
y103	-.2971837	1.062232	-0.28	0.806	-4.867598	4.27323
_cons	.0100096	.0062548	1.60	0.251	-.0169026	.0369218

```

. test y102 y103
( 1) y102 = 0
( 2) y103 = 0
      F( 2, 1530) = 4.07
      Prob > F = 0.1972

```

. \*11 test all actual and season variables inflow

. reg ln b x7 x8 x9 x10 x11 x12,robust cluster(PD)

Linear regression Number of obs = **1533**  
 F( 1, 2) = .  
 Prob > F = .  
 R-squared = **0.1858**  
 Root MSE = **.27539**

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x7	<b>-.0240995</b>	<b>.0068199</b>	<b>-3.53</b>	<b>0.072</b>	<b>-.0534432</b>	<b>.0052442</b>
x8	<b>.0143216</b>	<b>.0033682</b>	<b>4.25</b>	<b>0.051</b>	<b>-.0001707</b>	<b>.0288138</b>
x9	<b>.0165504</b>	<b>.0050151</b>	<b>3.30</b>	<b>0.081</b>	<b>-.005028</b>	<b>.0381288</b>
x10	<b>-.002278</b>	<b>.0006885</b>	<b>-3.31</b>	<b>0.080</b>	<b>-.0052403</b>	<b>.0006844</b>
x11	<b>-.0108104</b>	<b>.0027374</b>	<b>-3.95</b>	<b>0.059</b>	<b>-.0225886</b>	<b>.0009679</b>
x12	<b>.0048048</b>	<b>.0009229</b>	<b>5.21</b>	<b>0.035</b>	<b>.0008338</b>	<b>.0087757</b>
_cons	<b>-.0254956</b>	<b>.0148593</b>	<b>-1.72</b>	<b>0.228</b>	<b>-.0894298</b>	<b>.0384386</b>

. test x7 x9 x11

( 1) **x7 = 0**  
 ( 2) **x9 = 0**  
 ( 3) **x11 = 0**  
 Constraint 3 dropped  
 F( 2, 2) = **9.33**  
 Prob > F = **0.0968**

. test x8 x10 x12

( 1) **x8 = 0**  
 ( 2) **x10 = 0**  
 ( 3) **x12 = 0**  
 Constraint 3 dropped  
 F( 2, 2) = **33.78**  
 Prob > F = **0.0288**

. predict u11,r

. predict y11hat,xb

. reg ln b x7 x8 x9 x10 x11 x12 l.u11,robust cluster(PD)

Linear regression Number of obs = **1530**  
 F( 1, 2) = .  
 Prob > F = .  
 R-squared = **0.2022**  
 Root MSE = **.27294**

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x7	<b>-.0245768</b>	<b>.0072024</b>	<b>-3.41</b>	<b>0.076</b>	<b>-.0555663</b>	<b>.0064128</b>
x8	<b>.0138528</b>	<b>.0032293</b>	<b>4.29</b>	<b>0.050</b>	<b>-.0000419</b>	<b>.0277475</b>
x9	<b>.0175578</b>	<b>.0056594</b>	<b>3.10</b>	<b>0.090</b>	<b>-.0067926</b>	<b>.0419083</b>
x10	<b>-.0022709</b>	<b>.0007179</b>	<b>-3.16</b>	<b>0.087</b>	<b>-.0053599</b>	<b>.0008182</b>
x11	<b>-.011326</b>	<b>.003065</b>	<b>-3.70</b>	<b>0.066</b>	<b>-.0245138</b>	<b>.0018618</b>
x12	<b>.0049474</b>	<b>.0009669</b>	<b>5.12</b>	<b>0.036</b>	<b>.000787</b>	<b>.0091078</b>
u11						
l1.	<b>-.1434048</b>	<b>.0183409</b>	<b>-7.82</b>	<b>0.016</b>	<b>-.2223192</b>	<b>-.0644904</b>
_cons	<b>-.0246622</b>	<b>.0166768</b>	<b>-1.48</b>	<b>0.277</b>	<b>-.0964166</b>	<b>.0470922</b>

```

. gen y112=y11hat*y11hat
.
. gen y113=y112*y11hat
.
. reg lnb x7 x8 x9 x10 x11 x12 y112 y113, robust cluster(PD)
Linear regression                               Number of obs =   1533
                                                F( 1, 2) = .
                                                Prob > F = .
                                                R-squared = 0.2371
                                                Root MSE = 0.26675

```

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x7	-.0295715	.0067831	-4.36	0.049	-.0587566	-.0003863
x8	.0199639	.0042467	4.70	0.042	.0016918	.0382359
x9	.0184686	.0046442	3.98	0.058	-.0015138	.038451
x10	-.0027316	.0007915	-3.45	0.075	-.0061373	.0006742
x11	-.012285	.0025118	-4.89	0.039	-.0230925	-.0014775
x12	.0065816	.0010471	6.29	0.024	.0020763	.011087
y112	-1.471135	.7598279	-1.94	0.192	-4.74041	1.798141
y113	-.171372	.3107594	-0.55	0.637	-1.508462	1.165718
_cons	-.0391129	.0180197	-2.17	0.162	-.1166457	.0384198

```

. test y112 y113
( 1) y112 = 0
( 2) y113 = 0
      F( 2, 2) = 241.95
      Prob > F = 0.0041

```

. \*12 test all actual and season variables snow

. reg lnb x13 x14,robust cluster(PD)

Linear regression

Number of obs =	1533
F( 1, 2) =	.
Prob > F =	.
R-squared =	0.1787
Root MSE =	.27622

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x13	-1.83e-06	4.40e-07	-4.17	0.053	-3.73e-06	5.91e-08
x14	1.83e-06	4.19e-07	4.36	0.049	2.50e-08	3.63e-06
_cons	-0.003071	.0022393	-0.14	0.903	-0.0099418	.0093277

. predict u12,r

. predict y12hat,xb

. reg lnb x13 x14 l.u12,robust cluster(PD)

Linear regression

Number of obs =	1530
F( 1, 2) =	.
Prob > F =	.
R-squared =	0.1790
Root MSE =	.27651

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x13	-1.84e-06	4.43e-07	-4.15	0.053	-3.74e-06	6.78e-08
x14	1.83e-06	4.15e-07	4.40	0.048	4.21e-08	3.62e-06
u12						
l1.	-.0201593	.0332214	-0.61	0.606	-.1630993	.1227808
_cons	.0003219	.0030487	0.11	0.926	-.0127957	.0134396

. gen y122=y12hat\*y12hat

. gen y123=y122\*y12hat

. reg lnb x13 x14 y122 y123, robust cluster(PD)

Linear regression

Number of obs =	1533
F( 1, 2) =	.
Prob > F =	.
R-squared =	0.2196
Root MSE =	.26944

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x13	-2.80e-06	5.02e-07	-5.56	0.031	-4.96e-06	-6.34e-07
x14	2.78e-06	4.78e-07	5.81	0.028	7.22e-07	4.83e-06
y122	.4046085	.220562	1.83	0.208	-.544393	1.35361
y123	-5.248198	1.634523	-3.21	0.085	-12.28098	1.784585
_cons	.0033745	.001283	2.63	0.119	-.0021459	.008895

. test y122 y123

( 1) y122 = 0

( 2) y123 = 0

F( 2, 2) =	5.21
Prob > F =	0.1609



. \*13 Test all diff. variables

. reg lnb x15 x16 x17 x18 x19 x20 x21,robust cluster(PD)

Linear regression Number of obs = 1533  
F( 1, 2) = .  
Prob > F = .  
R-squared = 0.4366  
Root MSE = .22916

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x15	.0028822	.0006046	4.77	0.041	.0002809	.0054834
x16	-.0004454	.0001286	-3.46	0.074	-.0009986	.0001078
x17	.0001677	.0000886	1.89	0.199	-.0002135	.0005489
x18	.0055573	.0014118	3.94	0.059	-.0005172	.0116319
x19	-.0013973	.0005307	-2.63	0.119	-.0036809	.0008863
x20	.0015506	.0003501	4.43	0.047	.0000441	.0030572
x21	9.71e-07	2.68e-07	3.62	0.068	-1.82e-07	2.12e-06
_cons	.0219707	.0075224	2.92	0.100	-.0103956	.0543371

. test x15 x16 x17

( 1) x15 = 0  
( 2) x16 = 0  
( 3) x17 = 0  
Constraint 2 dropped  
F( 2, 2) = 27.34  
Prob > F = 0.0353

. test x18 x19 x20

( 1) x18 = 0  
( 2) x19 = 0  
( 3) x20 = 0  
Constraint 3 dropped  
F( 2, 2) = 20.00  
Prob > F = 0.0476

. predict u13,r

. predict y13hat,xb

. reg lnb x15 x16 x17 x18 x19 x20 x21 l.u13,robust cluster(PD)

Linear regression Number of obs = 1530  
F( 1, 2) = .  
Prob > F = .  
R-squared = 0.4372  
Root MSE = .22933

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x15	.0029133	.000594	4.90	0.039	.0003577	.005469
x16	-.000454	.0001261	-3.60	0.069	-.0009964	.0000884
x17	.0001484	.0000952	1.56	0.260	-.0002614	.0005582
x18	.0055113	.0014115	3.90	0.060	-.000562	.0115846
x19	-.001276	.0006423	-1.99	0.185	-.0040397	.0014877
x20	.0014975	.000405	3.70	0.066	-.0002451	.0032401
x21	9.72e-07	2.59e-07	3.75	0.064	-1.43e-07	2.09e-06
u13						
l1.	.0255233	.0453425	0.56	0.630	-.1695696	.2206163
_cons	.0223713	.0074808	2.99	0.096	-.009816	.0545587

```

. gen y132=y13hat*y13hat
.
. gen y133=y132*y13hat
.
. reg lnb x15 x16 x17 x18 x19 x20 x21 y132 y133, robust cluster(PD)
Linear regression                               Number of obs = 1533
                                                F( 1, 2) = .
                                                Prob > F = .
                                                R-squared = 0.4453
                                                Root MSE = .22752
                                                (Std. Err. adjusted for 3 clusters in PD)

```

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x15	.0032147	.0009939	3.23	0.084	-.0010617	.0074912
x16	-.0006055	.0002037	-2.97	0.097	-.001482	.000271
x17	.0003246	.000155	2.09	0.171	-.0003423	.0009916
x18	.0048312	.0024488	1.97	0.187	-.0057052	.0153677
x19	-.0006531	.0007416	-0.88	0.471	-.003844	.0025379
x20	.001347	.0005695	2.37	0.142	-.0011034	.0037974
x21	9.45e-07	3.84e-07	2.46	0.133	-7.09e-07	2.60e-06
y132	.4296539	.0605893	7.09	0.019	.168959	.6903487
y133	-.2346582	1.114206	-0.21	0.853	-5.028698	4.559382
_cons	.0081576	.0022282	3.66	0.067	-.0014296	.0177448

```

. test y132 y133
( 1) y132 = 0
( 2) y133 = 0
      F( 2, 2) = 26.20
      Prob > F = 0.0368

```

. \*14 Test diff. variables reservoir level

. reg lnb x15 x16 x17,robust cluster(PD)

Linear regression Number of obs = 1533  
F( 1, 2) = .  
Prob > F = .  
R-squared = 0.3701  
Root MSE = .24198

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x15	.0032127	.0007114	4.52	0.046	.0001516	.0062738
x16	-.0002325	.0000984	-2.36	0.142	-.0006558	.0001908
x17	.000371	.0000704	5.27	0.034	.0000681	.0006739
_cons	.0256769	.0081687	3.14	0.088	-.00947	.0608239

. predict u14,r

. predict y14hat,xb

. reg lnb x15 x16 x17 l.u14,robust cluster(PD)

Linear regression Number of obs = 1530  
F( 1, 2) = .  
Prob > F = .  
R-squared = 0.3732  
Root MSE = .24169

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x15	.003207	.0006995	4.58	0.044	.0001971	.0062168
x16	-.0002713	.0001136	-2.39	0.139	-.0007599	.0002172
x17	.0003938	.0000675	5.83	0.028	.0001032	.0006844
u14						
l1.	-.0580686	.0142987	-4.06	0.056	-.1195908	.0034535
_cons	.0262424	.0090583	2.90	0.101	-.0127323	.065217

. gen y142=y14hat\*y14hat

. gen y143=y142\*y14hat

. reg lnb x15 x16 x17 y142 y143, robust cluster(PD)

Linear regression Number of obs = 1533  
F( 1, 2) = .  
Prob > F = .  
R-squared = 0.3749  
Root MSE = .24121

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x15	.0031625	.0011018	2.87	0.103	-.001578	.007903
x16	-.0002641	.0001404	-1.88	0.201	-.0008683	.0003402
x17	.000501	.0001801	2.78	0.109	-.0002738	.0012757
y142	.4761651	.0203048	23.45	0.002	.3888008	.5635295
y143	.4218255	.9251132	0.46	0.693	-3.558615	4.402266
_cons	.0121393	.0020053	6.05	0.026	.0035113	.0207674

. test y142 y143

( 1) y142 = 0

( 2) y143 = 0

F( 2, 2) = 289.11  
Prob > F = 0.0034

. \*15 Test diff. variables inflow

. reg lnb x18 x19 x20,robust cluster(PD)

Linear regression Number of obs = 1533  
F( 1, 2) = .  
Prob > F = .  
R-squared = 0.1363  
Root MSE = .28335

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x18	.0153809	.0036108	4.26	0.051	-.0001551	.0309168
x19	-.0043394	.0011283	-3.85	0.061	-.0091942	.0005155
x20	.0055052	.0010891	5.06	0.037	.0008194	.010191
_cons	-.0016957	.0021404	-0.79	0.511	-.0109051	.0075136

. predict u15,r

. predict y15hat,xb

. reg lnb x18 x19 x20 l.u15,robust cluster(PD)

Linear regression Number of obs = 1530  
F( 1, 2) = .  
Prob > F = .  
R-squared = 0.1385  
Root MSE = .28335

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x18	.0152579	.0035235	4.33	0.049	.0000973	.0304184
x19	-.0044289	.0012103	-3.66	0.067	-.0096363	.0007785
x20	.0055802	.0011502	4.85	0.040	.0006312	.0105291
u15						
l1.	-.0517033	.0257488	-2.01	0.182	-.1624914	.0590849
_cons	-.0017472	.0023155	-0.75	0.529	-.0117098	.0082154

. gen y152=y15hat\*y15hat

. gen y153=y152\*y15hat

. reg lnb x15 x16 x17 y152 y153, robust cluster(PD)

Linear regression Number of obs = 1533  
F( 1, 2) = .  
Prob > F = .  
R-squared = 0.3817  
Root MSE = .23989

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x15	.0032943	.0007428	4.44	0.047	.0000985	.0064901
x16	-.0002939	.0001042	-2.82	0.106	-.0007422	.0001545
x17	.0004029	.0000798	5.05	0.037	.0000596	.0007462
y152	1.359316	.4357825	3.12	0.089	-.5157052	3.234336
y153	-1.341301	.5825888	-2.30	0.148	-3.847978	1.165376
_cons	.0117486	.0031791	3.70	0.066	-.0019301	.0254273

. test y152 y153

( 1) y152 = 0

( 2) y153 = 0

F( 2, 2) = 5363.23  
Prob > F = 0.0002

. \*16 Test diff. variables snow

. reg lnb x21,robust cluster(PD)

Linear regression

Number of obs = 1533  
 F( 1, 2) = 19.04  
 Prob > F = 0.0487  
 R-squared = 0.1787  
 Root MSE = .27613

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x21	1.83e-06	4.19e-07	4.36	0.049	2.54e-08	3.63e-06
_cons	-.0013408	.0021174	-0.63	0.591	-.0104511	.0077694

. predict u16,r

. predict y16hat,xb

. reg lnb x21 l.u16,robust cluster(PD)

Linear regression

Number of obs = 1530  
 F( 1, 2) = .  
 Prob > F = .  
 R-squared = 0.1790  
 Root MSE = .27643

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x21	1.83e-06	4.15e-07	4.40	0.048	4.15e-08	3.62e-06
u16						
l1.	-.019567	.0304112	-0.64	0.586	-.1504157	.1112818
_cons	-.001454	.0021896	-0.66	0.575	-.0108749	.0079668

. gen y162=y16hat\*y16hat

. gen y163=y162\*y16hat

. reg lnb x21 y162 y163, robust cluster(PD)

Linear regression

Number of obs = 1533  
 F( 1, 2) = .  
 Prob > F = .  
 R-squared = 0.2195  
 Root MSE = .26937

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x21	2.77e-06	4.73e-07	5.86	0.028	7.38e-07	4.81e-06
y162	.3506806	.1260733	2.78	0.109	-.191769	.8931302
y163	-5.184976	1.50684	-3.44	0.075	-11.66839	1.298435
_cons	.0010732	.0023305	0.46	0.690	-.0089539	.0111004

. test y162 y163

( 1) y162 = 0

( 2) y163 = 0

F( 2, 2) = 8.11  
 Prob > F = 0.1098

```
. *17 test all actual variables and diff. variables
.
. reg lnb x2 x4 x6 x8 x10 x12 x14 x15 x16 x17 x18 x19 x20 x21,robust cluster(PD)
```

```
Linear regression                               Number of obs =   1533
                                                F( 2, 1530) =      .
                                                Prob > F         =
                                                R-squared       =   0.5101
                                                Root MSE       =   .21418

                                                (Std. Err. adjusted for 3 clusters in PD)
```

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]
x2	-.0071979	.0017371	-4.14	0.054	-.014672 .0002761
x4	.013412	.0030588	4.38	0.048	.000251 .026573
x6	-.0065101	.001373	-4.74	0.042	-.0124179 -.0006024
x8	.0002852	.0006734	0.42	0.713	-.0026121 .0031825
x10	.0013777	.000838	1.64	0.242	-.0022277 .0049832
x12	.0014304	.0009138	1.57	0.258	-.0025015 .0053624
x14	2.70e-06	5.81e-07	4.65	0.043	1.99e-07 5.20e-06
x15	.0101789	.0023646	4.30	0.050	4.74e-06 .020353
x16	-.0139057	.0031739	-4.38	0.048	-.0275619 -.0002496
x17	.0067525	.0013697	4.93	0.039	.0008593 .0126458
x18	.0040694	.000431	9.44	0.011	.0022148 .005924
x19	-.0006952	.0008295	-0.84	0.490	-.0042642 .0028738
x20	-.0005892	.0008147	-0.72	0.545	-.0040944 .002916
x21	-1.76e-06	3.20e-07	-5.50	0.032	-3.14e-06 -3.82e-07
_cons	-.0108401	.0094422	-1.15	0.370	-.0514665 .0297863

```
. test x2 x4 x6 x15 x16 x17
( 1) x2 = 0
( 2) x4 = 0
( 3) x6 = 0
( 4) x15 = 0
( 5) x16 = 0
( 6) x17 = 0
Constraint 1 dropped
Constraint 2 dropped
Constraint 3 dropped
Constraint 4 dropped
F( 2, 1530) = 45.19
Prob > F = 0.0216
```

```
. test x2 x4 x6
( 1) x2 = 0
( 2) x4 = 0
( 3) x6 = 0
Constraint 3 dropped
F( 2, 1530) = 68.05
Prob > F = 0.0145
```

```
. test x15 x16 x17
( 1) x15 = 0
( 2) x16 = 0
( 3) x17 = 0
Constraint 1 dropped
F( 2, 1530) = 45.19
Prob > F = 0.0216
```

```
. test x8 x10 x12 x18 x19 x20
( 1) x8 = 0
( 2) x10 = 0
( 3) x12 = 0
( 4) x18 = 0
( 5) x19 = 0
( 6) x20 = 0
Constraint 1 dropped
Constraint 2 dropped
Constraint 5 dropped
Constraint 6 dropped
F( 2, 1530) = 78.55
Prob > F = 0.0126
```

```
. test x8 x10 x12
( 1) x8 = 0
( 2) x10 = 0
( 3) x12 = 0
Constraint 1 dropped
F( 2, 1530) = 1100.91
Prob > F = 0.0009
```

```
. test x18 x19 x20
( 1) x18 = 0
( 2) x19 = 0
( 3) x20 = 0
Constraint 3 dropped
F( 2, 1530) = 89.46
Prob > F = 0.0111
```

```
. test x14 x21
( 1) x14 = 0
( 2) x21 = 0
F( 2, 1530) = 635.63
Prob > F = 0.0016
```

```

. predict u17,r
.
. predict y17hat,xb
.
. reg lnb x2 x4 x6 x8 x10 x12 x14 x15 x16 x17 x18 x19 x20 x21 l.u17,robust cluste
> r(PD)

```

Linear regression

Number of obs =	1530
F( 1, 2) =	.
Prob > F =	.
R-squared =	0.5192
Root MSE =	.21246

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	-.0072884	.0018608	-3.92	0.059	-.0152946	.0007179
x4	.0136963	.0033164	4.13	0.054	-.0005731	.0279656
x6	-.0067193	.0015201	-4.42	0.048	-.0132599	-.0001787
x8	-.0006364	.0006673	-0.95	0.441	-.0035074	.0022347
x10	.0023978	.0007674	3.12	0.089	-.0009043	.0056998
x12	.0011279	.0009256	1.22	0.347	-.0028547	.0051105
x14	2.76e-06	6.25e-07	4.41	0.048	6.88e-08	5.45e-06
x15	.0101747	.0024325	4.18	0.053	-.0002914	.0206408
x16	-.0141709	.0034241	-4.14	0.054	-.0289035	.0005616
x17	.007049	.0015435	4.57	0.045	.0004079	.0136901
x18	.0049179	.0006192	7.94	0.015	.0022537	.0075821
x19	-.0019312	.0007282	-2.65	0.118	-.0050642	.0012018
x20	-.0000791	.0008208	-0.10	0.932	-.0036107	.0034525
x21	-1.86e-06	3.73e-07	-4.98	0.038	-3.46e-06	-2.54e-07
u17						
l1.	-.1401945	.0287504	-4.88	0.040	-.2638975	-.0164916
_cons	-.0095036	.0102016	-0.93	0.450	-.0533974	.0343902

```

. gen y172=y17hat*y17hat
.
. gen y173=y172*y17hat
.
. reg lnb x2 x4 x6 x8 x10 x12 x14 x15 x16 x17 x18 x19 x20 x21 y172 y173, robust c
> luster(PD)

```

Linear regression

Number of obs =	1533
F( 1, 2) =	.
Prob > F =	.
R-squared =	0.5141
Root MSE =	.21343

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	-.0079855	.002795	-2.86	0.104	-.0200113	.0040404
x4	.0148731	.0050474	2.95	0.098	-.0068442	.0365904
x6	-.0072325	.0023815	-3.04	0.093	-.0174792	.0030143
x8	.0014364	.0021885	0.66	0.579	-.0079801	.0108529
x10	.0009476	.0012571	0.75	0.530	-.0044614	.0063566
x12	.0016926	.0011921	1.42	0.291	-.0034365	.0068216
x14	3.00e-06	9.86e-07	3.04	0.093	-1.24e-06	7.24e-06
x15	.0111877	.003713	3.01	0.095	-.0047883	.0271636
x16	-.0153728	.0051554	-2.98	0.096	-.0375545	.0068089
x17	.0075238	.0024892	3.02	0.094	-.0031865	.018234
x18	.0039359	.0004625	8.51	0.014	.001946	.0059258
x19	-.0004127	.0010949	-0.38	0.742	-.0051237	.0042984
x20	-.0006804	.0008766	-0.78	0.519	-.004452	.0030911
x21	-1.97e-06	6.13e-07	-3.21	0.085	-4.61e-06	6.67e-07
y172	-.0677094	.069615	-0.97	0.433	-.3672383	.2318196
y173	-.4966709	.8341538	-0.60	0.612	-4.085745	3.092403
_cons	-.0129478	.0085321	-1.52	0.268	-.0496587	.023763

```

. test y172 y173
( 1) y172 = 0
( 2) y173 = 0

F( 2, 2) = 1.14
Prob > F = 0.4666

```

. \*18 test all actual variables and diff. variables reservoir level

. reg lnb x2 x4 x6 x15 x16 x17,robust cluster(PD)

Linear regression Number of obs = 1533  
F( 1, 2) = .  
Prob > F = .  
R-squared = 0.4006  
Root MSE = .23628

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	-.0013281	.0003154	-4.21	0.052	-.002685	.0000289
x4	.0009654	.0002531	3.81	0.062	-.0001235	.0020544
x6	.0005444	.0001061	5.13	0.036	.000088	.0010008
x15	.0043875	.0009882	4.44	0.047	.0001354	.0086395
x16	-.0011368	.0003021	-3.76	0.064	-.0024366	.000163
x17	-.0000481	.0000959	-0.50	0.666	-.0004608	.0003646
_cons	.0066388	.0060869	1.09	0.389	-.0195511	.0328287

. test x2 x4 x6

( 1) x2 = 0  
( 2) x4 = 0  
( 3) x6 = 0  
Constraint 3 dropped  
F( 2, 2) = 55.28  
Prob > F = 0.0178

. test x15 x16 x17

( 1) x15 = 0  
( 2) x16 = 0  
( 3) x17 = 0  
Constraint 2 dropped  
F( 2, 2) = 15.65  
Prob > F = 0.0601

. predict u18,r

. predict y18hat,xb

. reg lnb x2 x4 x6 x15 x16 x17 l.u18,robust cluster(PD)

Linear regression Number of obs = 1530  
F( 1, 2) = .  
Prob > F = .  
R-squared = 0.4122  
Root MSE = .23429

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	-.0014233	.0003776	-3.77	0.064	-.0030481	.0002015
x4	.0010554	.0003131	3.37	0.078	-.0002918	.0024026
x6	.0005572	.0001129	4.94	0.039	.0000716	.0010429
x15	.0044048	.0010134	4.35	0.049	.0000447	.0087649
x16	-.0012981	.0003755	-3.46	0.074	-.002914	.0003177
x17	.0000459	.0000639	0.72	0.547	-.0002291	.0003208
u18						
l1.	-.1381865	.0194263	-7.11	0.019	-.2217711	-.054602
_cons	.0082612	.0076983	1.07	0.396	-.0248621	.0413845



```

. gen y182=y18hat*y18hat
.
. gen y183=y182*y18hat
.
. reg lnb x2 x4 x6 x15 x16 x17 y182 y183, robust cluster(PD)
Linear regression                               Number of obs =   1533
                                                F( 1, 1531) =      .
                                                Prob > F       =
                                                R-squared     =  0.4022
                                                Root MSE     =  0.23613

```

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x2	-.0014475	.0006331	-2.29	0.150	-.0041714	.0012764
x4	.0010751	.0004988	2.16	0.164	-.001071	.0032212
x6	.000545	.0002067	2.64	0.119	-.0003444	.0014344
x15	.0046353	.001743	2.66	0.117	-.0028644	.012135
x16	-.0012469	.0005846	-2.13	0.167	-.003762	.0012683
x17	.0000572	.0000657	0.87	0.475	-.0002253	.0003398
y182	.1210432	.0452684	2.67	0.116	-.0737308	.3158173
y183	-.2974024	1.062301	-0.28	0.806	-4.868116	4.273311
_cons	.0100114	.0062574	1.60	0.251	-.0169118	.0369347

```

. test y182 y183
( 1) y182 = 0
( 2) y183 = 0
      F( 2, 1531) =  4.07
      Prob > F =  0.1973

```

. \*19 test all actual variables and diff. variables inflow

. reg lnb x8 x10 x12 x18 x19 x20,robust cluster(PD)

Linear regression

Number of obs = 1533  
 F( 1, 2) = .  
 Prob > F = .  
 R-squared = 0.1855  
 Root MSE = .27544

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x8	-.009693	.003796	-2.55	0.125	-.0260257	.0066397
x10	.0141832	.0044438	3.19	0.086	-.0049371	.0333034
x12	-.005966	.0018783	-3.18	0.086	-.0140479	.0021159
x18	.0240069	.0068202	3.52	0.072	-.005338	.0533517
x19	-.0164625	.0050176	-3.28	0.082	-.0380517	.0051266
x20	.0107796	.0027389	3.94	0.059	-.0010049	.022564
_cons	-.0258165	.0150553	-1.71	0.229	-.0905941	.038961

. test x8 x10 x12

( 1) x8 = 0  
 ( 2) x10 = 0  
 ( 3) x12 = 0  
 Constraint 3 dropped  
 F( 2, 2) = 18.05  
 Prob > F = 0.0525

. test x18 x19 x20

( 1) x18 = 0  
 ( 2) x19 = 0  
 ( 3) x20 = 0  
 Constraint 3 dropped  
 F( 2, 2) = 9.36  
 Prob > F = 0.0966

. predict u19,r

. predict y19hat,xb

. reg lnb x8 x10 x12 x18 x19 x20 l.u19,robust cluster(PD)

Linear regression

Number of obs = 1530  
 F( 1, 2) = .  
 Prob > F = .  
 R-squared = 0.2019  
 Root MSE = .273

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x8	-.0106333	.0042792	-2.48	0.131	-.0290453	.0077787
x10	.0151922	.0050539	3.01	0.095	-.006553	.0369374
x12	-.0063373	.0021702	-2.92	0.100	-.0156748	.0030002
x18	.0244778	.0072034	3.40	0.077	-.0065159	.0554716
x19	-.0174631	.005661	-3.08	0.091	-.0418205	.0068943
x20	.0112925	.0030659	3.68	0.066	-.0018989	.0244838
u19						
l1.	-.1430972	.0183186	-7.81	0.016	-.2219157	-.0642786
_cons	-.0249885	.0169026	-1.48	0.277	-.0977146	.0477375

```

. gen y192=y19hat*y19hat
.
. gen y193=y192*y19hat
.
. reg lnb x8 x10 x12 x18 x19 x20 y192 y193, robust cluster(PD)
Linear regression                               Number of obs =   1533
                                                F( 1, 1531) =      .
                                                Prob > F       =
                                                R-squared     =  0.2368
                                                Root MSE     =  0.26679

```

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x8	-.0095827	.0033826	-2.83	0.105	-.0241371	.0049716
x10	.0157107	.0040851	3.85	0.061	-.0018661	.0332874
x12	-.0056869	.0016077	-3.54	0.071	-.0126045	.0012306
x18	.0295529	.0067901	4.35	0.049	.0003375	.0587683
x19	-.0184491	.0046536	-3.96	0.058	-.0384721	.0015738
x20	.0122796	.0025138	4.88	0.039	.0014636	.0230957
y192	-1.476474	.7645283	-1.93	0.193	-4.765974	1.813026
y193	-.1663776	.3159369	-0.53	0.651	-1.525744	1.192989
_cons	-.0393375	.0181451	-2.17	0.162	-.1174096	.0387347

```

. test y192 y193
( 1) y192 = 0
( 2) y193 = 0
      F( 2, 1531) = 262.71
      Prob > F = 0.0038

```

. \*20 test all actual variables and diff. variables snow

. reg lnb x14 x21,robust cluster(PD)

Linear regression

Number of obs =	1533
F( 1, 2) =	.
Prob > F =	.
R-squared =	0.1787
Root MSE =	.27622

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x14	-5.41e-09	2.10e-08	-0.26	0.820	-9.56e-08	8.48e-08
x21	1.83e-06	4.40e-07	4.17	0.053	-5.91e-08	3.73e-06
_cons	-0.003071	.0022393	-0.14	0.903	-0.0099418	.0093277

. predict u20,r

. predict y20hat,xb

. reg lnb x14 x21 l.u20,robust cluster(PD)

Linear regression

Number of obs =	1530
F( 1, 2) =	.
Prob > F =	.
R-squared =	0.1790
Root MSE =	.27651

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x14	-9.32e-09	2.78e-08	-0.33	0.770	-1.29e-07	1.10e-07
x21	1.84e-06	4.43e-07	4.15	0.053	-6.78e-08	3.74e-06
u20						
l1.	-.0201593	.0332214	-0.61	0.606	-.1630993	.1227808
_cons	.0003219	.0030487	0.11	0.926	-.0127957	.0134396

. gen y202=y20hat\*y20hat

. gen y203=y202\*y20hat

. reg lnb x14 x21 y202 y203, robust cluster(PD)

Linear regression

Number of obs =	1533
F( 1, 2) =	.
Prob > F =	.
R-squared =	0.2196
Root MSE =	.26944

(Std. Err. adjusted for 3 clusters in PD)

lnb	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
x14	-1.83e-08	2.64e-08	-0.69	0.561	-1.32e-07	9.54e-08
x21	2.80e-06	5.02e-07	5.56	0.031	6.34e-07	4.96e-06
y202	.4046083	.220562	1.83	0.208	-.5443932	1.35361
y203	-5.248198	1.634523	-3.21	0.085	-12.28098	1.784586
_cons	.0033745	.001283	2.63	0.119	-.0021459	.0088949

. test y202 y203

( 1) y202 = 0  
( 2) y203 = 0

F( 2, 2) =	5.21
Prob > F =	0.1609