Two-Way Fixed Effects, the Two-Way Mundlak Regression, and Event Study Estimators

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1. Introduction

- For panel data, two-way fixed effects (TWFE) is still a staple in empirical research.
  - Applied to "structural" models – say, production functions.
  - Applied to policy analysis – event studies.
- Used for all configurations of N and T.
- With small T, large N, time effects often absorbed into covariates.
  - Analyze as a one-way FE estimator.

- The one-way Mundlak regression has proven useful for many purposes.
  - ▸ Leads to simple, robust, regression-based comparisons between FE and random effects estimation: Arellano (1993).
  - ▸ Produces insight into the pre-testing problem with Hausman tests.
  - ▸ Suggests how to allow heterogeneity to correlate with covariates in nonlinear models: Mundlak-Chamberlain device.

- Wooldridge (2019, Journal of Econometrics): The one-way Mundlak regression applies to unbalanced panels.
  - In the linear case, Mundlak still produces the complete-cases FE estimator.
  - Suggests correlated random effects for heterogeneous slopes and nonlinear models.

- Current paper: Shows the equivalence between the TWFE estimator and the obvious two-way Mundlak regression.
  - ▸ In latter case, focus is on pooled OLS, but results also hold for RE.
- Equivalence is simple but useful.
  - ▸ Further reveals the workings of TWFE.
  - ▸ Applications to linear event study estimators with staggered intervention.
  - ▸ Applications to factor models.

- Advantages of TWFE for event studies:

1. We know properties of TWFE when the panel is unbalanced.
2. It is easy to test the null that treatment effects are homogeneous in a robust way.
3. Immediately extensions of the TWFE etimator to removing unit-specific trends can be applied with heterogenous treatment effects.

- Advantages of POLS for event studies:
  - Given equivalence in the linear case, POLS can be extended to nonlinear models.

2. Equivalence of TWFE and the Two-Way Mundlak Regression

- Motivation for TWFE estimation:

$$y_{it} = \mathbf{x}_{it}\boldsymbol{\beta} + c_i + f_t + u_{it}, \;\; t = 1, \ldots, T; \, i = 1, \ldots, N$$

  - $\mathbf{x}_{it}$ is $1 \times K$.
  - c_i are the unit-specific effects.
  - f_t are the time-specific effects.

- Results here are pure algebra.
- The two-way dummy variable regression:

$$y_{it} \text{ on } \mathbf{x}_{it}, 1, c2_i, ..., cN_i, f2_t, ..., fT_t, \;\; t = 1, \ldots, T; \; i = 1, \ldots, N.$$

  - Coefficients on $\mathbf{x}_{it}$ are $\hat{\boldsymbol{\beta}}_{FE}$ $(K \times 1)$.
- $\mathbf{x}_{it}$ only includes variables that have some variation across i and t.

- Baltagi (2001): Two-way within transformation gives $\hat{\boldsymbol{\beta}}_{FE}$.

$$\bar{\mathbf{x}}_{i\bullet} = T^{-1} \sum_{t=1}^{T} \mathbf{x}_{it}$$

$$\bar{\mathbf{x}}_{\bullet t} = N^{-1} \sum_{i=1}^{N} \mathbf{x}_{it}$$

$$\bar{\mathbf{x}} = (NT)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} \mathbf{x}_{it} = N^{-1} \sum_{i=1}^{N} \bar{\mathbf{x}}_{i\bullet} = T^{-1} \sum_{t=1}^{T} \bar{\mathbf{x}}_{\bullet t}$$

$$\ddot{\mathbf{x}}_{it} = (\mathbf{x}_{it} - \bar{\mathbf{x}}_{i\cdot}) - N^{-1}\sum_{i=1}^{N}(\mathbf{x}_{it} - \bar{\mathbf{x}}_{i\cdot}) = \mathbf{x}_{it} - \bar{\mathbf{x}}_{i\cdot} - \bar{\mathbf{x}}_{\cdot t} + \bar{\mathbf{x}}$$

$$\ddot{y}_{it} = y_{it} - \bar{y}_i - \bar{y}_t + \bar{y}$$

- $\hat{\boldsymbol{\beta}}_{FE}$ is also the pooled OLS estimator from

$$\ddot{y}_{it} \text{ on } \ddot{\mathbf{x}}_{it},\ t = 1, \ldots, T;\ i = 1, \ldots, N.$$

- Alternatively, consider the *two-way Mundlak regression*.
- Pooled OLS of

$$y_{it} \text{ on } 1, \mathbf{x}_{it}, \bar{\mathbf{x}}_{i\cdot}, \bar{\mathbf{x}}_{\cdot t},\ t = 1, \ldots, T; i = 1, \ldots, N.$$

  - Let $\hat{\boldsymbol{\beta}}_M$ be the coefficients $\mathbf{x}_{it}$.

THEOREM: Provided the $K \times K$ matrix

$$\sum_{i=1}^{N} \sum_{t=1}^{T} \ddot{\mathbf{x}}_{it}' \ddot{\mathbf{x}}_{it}$$

is nonsingular,

$$\hat{\boldsymbol{\beta}}_{M} = \hat{\boldsymbol{\beta}}_{FE}$$

Moreover, in the extended regression

$$y_{it} \text{ on } 1, \mathbf{x}_{it}, \bar{\mathbf{x}}_{i\cdot}, \bar{\mathbf{x}}_{\cdot t}, \mathbf{z}_{i}, \mathbf{m}_{t}, t = 1,\ldots,T; i = 1,\ldots,N$$

for time-constant variables $\mathbf{z}_i$ and unit-constant variables $\mathbf{m}_t$, the coefficients on $\mathbf{x}_{it}$ are still $\hat{\boldsymbol{\beta}}_{FE}$. $\square$

- Proof uses Frisch-Waugh partialling out.
- Coefficients on $\bar{\mathbf{x}}_{i\cdot}$ and $\bar{\mathbf{x}}_{\cdot t}$ do change with the inclusion of $\mathbf{z}_i$, $\mathbf{m}_t$.
  - Basis of robust, regression-based Hausman tests.
- Random effects-type estimators give the same conclusions.
- Suppose a regressor is an interaction of the form

$$x_{itj} = z_{ij} \cdot m_{tj}$$

  - Then

$$\bar{x}_{i\cdot j} = z_{ij} \cdot \bar{m}_j, \; \bar{x}_{\cdot tj} = \bar{z}_j m_{tj}$$

  - Mundlak regression includes z_{ij}, m_{tj} as controls.

3. Interventions with Common Treatment Timing

- T time periods.
  - $t = 1, \ldots, q-1$ are control periods.
  - Intervention happens at $t = q$, remains in place.
- Treatment indicator:

$$w_{it} = d_i \cdot p_t$$

$$d_i = 1 \text{ if (eventually) treated}$$

$$p_t = fq_t + \cdots + fT_t = 1 \text{ if a post treatment period}$$

- Homogeneous treatment effect.
- Equation that motivates TWFE:

$$y_{it} = \beta w_{it} + c_i + g_t + u_{it}, t = 1, \ldots, T; i = 1, 2, \ldots, N$$

$$\bar{w}_{i\cdot} = d_i \bar{p}$$
$$\bar{w}_{\cdot t} = \bar{d} p_t$$

- TWM regression is equivalent to the DID regression

$$y_{it} \text{ on } 1, w_{it}, d_i, p_t, t = 1, \ldots, T; i = 1, \ldots, N$$

  - ▸ $\hat{\beta}_{DD} = \hat{\beta}_{FE}$. Enough to control for d_i, p_t.

- The TWFE estimator has the familiar form

$$\hat{\beta}_{FE} = \hat{\beta}_{DD} = \left(\bar{y}_1^{post} - \bar{y}_0^{post}\right) - (\bar{y}_1^{pre} - \bar{y}_0^{pre})$$

- Using separate time dummies $f2_t$, ..., fT_t in place of p_t has no effect on $\hat{\beta}_{DD}$.

- Adding controls, $\mathbf{x}_i$ or $d_i \cdot \mathbf{x}_i$, has no effect on $\hat{\beta}_{DD}$.

- Now allow TEs to change over treatment period.

$$y_{it} = \beta_q(w_{it} \cdot fq_t) + \cdots + \beta_T(w_{it} \cdot fT_t) + c_i + g_t + u_{it}$$

- Can use TWFE to estimate the β_r.

$$w_{it} \cdot fr_t = d_i \cdot p_t \cdot fr_t = d_i(fq_t + \cdots + fT_t)fr_t = d_i fr_t$$

- Time averages are proportional to d_i.
- Cross-sectional averages proportional to fr_t.
- TWM equation:

$$y_{it} = \alpha + \beta_q(w_{it} \cdot fq_t) + \cdots + \beta_T(w_{it} \cdot fT_t) + \zeta d_i + \theta_q fq_t + \cdots + \theta_T fT_t + e_{it}$$

- POLS and RE give identical estimates.

- Add time-constant covariates, $\mathbf{x}_i$
- Coefficients on change with time period.
- Treatment effects change with t, $\mathbf{x}_i$, and possibly both:

$$
\begin{aligned}
y_{it} = {} & \beta_q(w_{it} \cdot fq_t) + \cdots + \beta_T(w_{it} \cdot fT_t) + [w_{it} \cdot fq_t \cdot (\mathbf{x}_i - \boldsymbol{\mu}_1)]\boldsymbol{\gamma}_q \\
& + \cdots + [w_{it} \cdot fT_t \cdot (\mathbf{x}_i - \boldsymbol{\mu}_1)]\boldsymbol{\gamma}_T \\
& + (fq_t \cdot \mathbf{x}_i)\boldsymbol{\delta}_q + \cdots + (fT_t \cdot \mathbf{x}_i)\boldsymbol{\delta}_T + c_i + g_t + u_{it}
\end{aligned}
$$

$$\boldsymbol{\mu}_1 \equiv E(\mathbf{x}_i | d_i = 1)$$

- Can estimate by TWFE or TWM.

- TWM includes the time-constant variables d_i, $\mathbf{x}_i$, $d_i \cdot \mathbf{x}_i$.
- Need time dummies for fq_t, ..., fT_t.

$$
\begin{aligned}
y_{it} = \alpha &+ \beta_q(w_{it} \cdot fq_t) + \cdots + \beta_T(w_{it} \cdot fT_t) + [w_{it} \cdot fq_t \cdot (\mathbf{x}_i - \boldsymbol{\mu}_1)]\boldsymbol{\gamma}_q \\
&+ \cdots + [w_{it} \cdot fT_t \cdot (\mathbf{x}_i - \boldsymbol{\mu}_1)]\boldsymbol{\gamma}_T \\
&+ (fq_t \cdot \mathbf{x}_i)\boldsymbol{\delta}_q + \cdots + (fT_t \cdot \mathbf{x}_i)\boldsymbol{\delta}_T + \zeta d_i + \mathbf{x}_i\boldsymbol{\xi} + (d_i \cdot \mathbf{x}_i)\boldsymbol{\lambda} \\
&+ \theta_q fq_t + \cdots + \theta_T fT_t + e_{it}
\end{aligned}
$$

- Replace $\boldsymbol{\mu}_1$ with $\bar{\mathbf{x}}_1 = N_1^{-1} \sum_{i=1}^{N} d_i \cdot \mathbf{x}_i$.
  - In principle, account for sampling error. See did_4.do.

- Can connect this to period-by-period regression adjustment.
- Use periods $1, \ldots, q-1$ as the control and then each $r \in \{q, q+1, \ldots, T\}$ in turn:
- Can estimate

$$
\begin{aligned}
y_{it} &= \alpha + \beta_r w_{it} + w_{it} \cdot (\mathbf{x}_i - \bar{\mathbf{x}}_1)\boldsymbol{\gamma}_r + (fr_t \cdot \mathbf{x}_i)\boldsymbol{\delta}_r \\
&\quad + \zeta d_i + d_i \cdot \mathbf{x}_i \boldsymbol{\lambda} + \theta_r fr_t + error_{it} \\
&t \in \{1, \ldots, q-1, r\},\ i = 1, \ldots, N
\end{aligned}
$$

by POLS.

- Parametric version of Callaway and Sant'Anna (2020), but regression in levels.
- Estimates are identical to pooling all time periods.
- Doing separately has advantage of using doubly robust estimators (IPW and RA).

- In using a canned package – such as Stata and its `margins` option – need to be careful about how to specify interactions.
- Regression should look like

$$
\begin{aligned}
&y_{it} \text{ on } 1, d_i, \mathbf{x}_i, d_i \cdot \mathbf{x}_i, fq_t, \ldots, fT_t, fq_t \cdot \mathbf{x}_i, \ldots, fT_t \cdot \mathbf{x}_i, \\
&\qquad w_{it} \cdot fq_t, \ldots, w_{it} \cdot fT_t, w_{it} \cdot fq_t \cdot \mathbf{x}_i, \ldots, w_{it} \cdot fT_t \cdot \mathbf{x}_i
\end{aligned}
$$

- Then use

```
margins, dydx(w) at(d = 1 fq = 1 fqp1 = 0
   ... fT = 0), subpop(if d == 1) vce(uncon)
margins, dydx(w) at(d = 1 fq = 0 fqp1 = 1
  ... fT = 0), subpop(if d == 1) vce(uncon)
margins, dydx(w) at(d = 1 fq = 0 fqp1 = 0
  ... fT = 1), subpop(if d == 1) vce(uncon)
```

- Same with TWFE.
- See did_4.do.

What is Being Estimated?

- Potential outcomes, $y_t(0)$ and $y_t(1)$.
- Treatment effect for a generic unit:

$$te_t = y_t(1) - y_t(0)$$

- We can identify the ATT in each treated period:

$$\tau_t \equiv E[y_t(1) - y_t(0)|d = 1], t = q, q+1, \ldots, T$$

Assumption CT (Common Trend): With the (eventually) treated indicator d,

$$E[y_t(0) - y_1(0)|d] = E[y_t(0) - y_1(0)] \equiv \theta_t,\ t = 2, \ldots, T. \ \square$$

• With covariates:

Assumption CCT (Conditional Common Trends): For treatment indicator d and covariates $\mathbf{x}$,

$$E[y_t(0) - y_1(0)|d, \mathbf{x}] = E[y_t(0) - y_1(0)|\mathbf{x}],\ t = 2, \ldots, T.\ \square$$

• Abadie (2005) uses this with $T = 2$.

• Similar to Callaway and Sant'Anna (2020); Sun and Abraham (2021); and others.

4. Staggered Treatments

- Wooldridge (2005): Studied robustness of FE to heterogeneous slopes.
  - Suggested some strategies to allow heterogeneity based on intensity.
- TWFE under recent scrutiny for staggered (and more general) interventions.

• de Chaisemartin and D'Haultfœuille (2020), Goodman-Bacon (2018), Callaway and Sant'Anna (2021), Sun and Abraham (2021).

• Previous analysis shows TWFE is fine in common intervention time case provided TEs are allowed to change across t and with $\mathbf{x}$.

• Can use TWFE or TWM in staggered case with lots of heterogeneity.

- First intervention period is $t = q$.
- Some units treated in each period after q, up to T.
- No reversibility.
- Define treatment cohorts by dummies: d_q, ..., d_T.
  - $d_r = 1$ if unit enters treatment in period r.
  - Essentially intensity indicators.

- At least two way to define treatment effects.

1. Have two potential outcomes again, but the TEs are

$$E[y_t(1) - y_t(0)|d_r = 1], r = q, \ldots, T; t = r, \ldots, T$$

2. Think of the intensities defining different potential outcomes:

$$\tau_{rt} \equiv E[y_t(r) - y_t(0)|d_r = 1],\ r = q, \ldots, T; t = r, \ldots, T$$

- Second is easier to deal with.
  - Both lead to the same estimating equation.

Assumption CTS (**Common Trend**, **Staggered**): With the exposure dummies d_q, ..., d_T,

$$E[y_t(0) - y_1(0)|d_q,\ldots,d_T] = E[y_t(0) - y_1(0)] \equiv \theta_t,\ t = 2,\ldots,T.\ \square$$

- Again, similar to Callaway and Sant'Anna; Sun and Abraham; others.
- The paper derives the following for all t:

$$E(y_{it}|\mathbf{d}_i) = \eta + \lambda_q d_{iq} + \cdots + \lambda_T d_{iT} + \sum_{s=2}^{T} \theta_s fs_t$$

$$+ \sum_{r=q}^{T} \sum_{s=r}^{T} \tau_{rs}(w_{it} \cdot d_{ir} \cdot fs_t)$$

- This is the Mundlak equation.
  - Time dummies for $t < q$ are redundant.
- Mundlak regression:

$$
\begin{aligned}
y_{it} \text{ on } & 1, d_{iq}, ..., d_{iT}, fq_t, ..., fT_t, \\
& w_{it} \cdot d_{iq} \cdot fq_t, ..., w_{it} \cdot d_{iq} \cdot fT_t, \ ..., w_{it} \cdot d_{iT} \cdot fT_t
\end{aligned}
$$

- Equivalently, can use TWFE and drop everything except

$$
w_{it} \cdot d_{iq} \cdot fq_t, ..., w_{it} \cdot d_{iq} \cdot fT_t, \ ..., w_{it} \cdot d_{iT} \cdot fT_t
$$

- In practice, may need to impose commonality across cohort/time.

- Add covariates.

Assumption CCTS (**Conditional Common Trends**, **Staggered**):
For exposure indicators d_r and covariates $\mathbf{x}$,

$$E[y_t(0) - y_1(0)|d_q, \ldots, d_T, \mathbf{x}] = E[y_t(0) - y_1(0)|\mathbf{x}],\ t = 2, \ldots, T. \ \square$$

- Assume all conditional expectations are linear in $\mathbf{x}$.
- This means linearity conditional on each $d_r = 1$, $r = q, \ldots, T$.

$$\dot{\mathbf{x}}_r \equiv \mathbf{x} - E(\mathbf{x}|d_r = 1),\ r = q, \ldots, T$$

• Paper derives

$$
\begin{aligned}
E(y_t|d_q,\ldots,d_T,\mathbf{x}) &= \eta + \sum_{r=q}^{T}\lambda_r d_r + \mathbf{x}\boldsymbol{\kappa} + \sum_{r=q}^{T}(d_r \cdot \mathbf{x})\boldsymbol{\zeta}_r \\
&\quad + \sum_{s=2}^{T}\theta_s fs_t + \sum_{s=2}^{T}(fs_t \cdot \mathbf{x})\boldsymbol{\pi}_t \\
&\quad + \sum_{r=q}^{T}\sum_{s=r}^{T}\tau_{rs}(d_r \cdot fs_t) + \sum_{r=q}^{T}\sum_{s=r}^{T}(d_r \cdot fs_t \cdot \dot{\mathbf{x}}_r)\boldsymbol{\rho}_{rs}.
\end{aligned}
$$

• Słoczyński (forthcoming, REStat) in cross-sectional case with unconfoundness: Can be important to allow for slope heterogeneity.

- The regression is

$$
\begin{aligned}
y_{it} \text{ on } & 1, d_{iq}, ..., d_{iT}, \mathbf{x}_i, d_{iq} \cdot \mathbf{x}_i, ..., d_{iT} \cdot \mathbf{x}_i, \\
& fq_t, ..., fT_t, fq_t \cdot \mathbf{x}_i, ..., fT_t \cdot \mathbf{x}_i, \\
& w_{it} \cdot d_{iq} \cdot fq_t, ..., w_{it} \cdot d_{iq} \cdot fT_t, ..., \\
& w_{it} \cdot d_{i,q+1} \cdot f(q+1)_t, ..., w_{it} \cdot d_{i,q+1} \cdot fT_t, ..., w_{it} \cdot d_{iT} \cdot fT_t, \\
& w_{it} \cdot d_{iq} \cdot fq_t \cdot \dot{\mathbf{x}}_{iq}, ..., w_{it} \cdot d_{iq} \cdot fT_t \cdot \dot{\mathbf{x}}_{iT}, \\
& w_{it} \cdot d_{i,q+1} \cdot f(q+1)_t \cdot \dot{\mathbf{x}}_{iq}, ..., w_{it} \cdot d_{i,q+1} \cdot fT_t \cdot \dot{\mathbf{x}}_{iT}, ..., \\
& w_{it} \cdot d_{iT} \cdot fT_t \cdot \dot{\mathbf{x}}_{iT}
\end{aligned}
$$

$$
\dot{\mathbf{x}}_{ir} = \mathbf{x}_i - \bar{\mathbf{x}}_r = \mathbf{x}_i - N_r^{-1} \sum_{h=1}^{N} d_{hr} \mathbf{x}_h .
$$

- RE gives identical estimates.
  - Improving over POLS requires allowing more general patterns of serial correlation and maybe time-varying variances.
- Or drop everything in the first line except $fq_t \cdot \mathbf{x}_i$, ..., $fT_t \cdot \mathbf{x}_i$ and use TWFE.
  - Numerically identical.
- Can use Stata and `margins` to account for sampling variation in $\bar{\mathbf{x}}_r$.
  - See staggered_6.do.

5. Nonlinear Models

- With small T, TWFE cannot be applied to most nonlinear models.
  - Exception is Poisson regression.
- The pooled OLS methods extend to any nonlinear model.
- Suppose $y_{it} \geq 0$.

- Exponential mean is natural:

$$E(y_{it}|d_{iq},\ldots,d_{iT}) = \exp\Bigg[\eta + \lambda_q d_{iq} + \cdots + \lambda_T d_{iT} + \sum_{s=2}^{T}\theta_s fs_t + \sum_{r=q}^{T}\sum_{s=r}^{T}\tau_{rs}(w_{it}\cdot d_{ir}\cdot fs_t)\Bigg]$$

- Can be estimated by pooled Poisson.
  - Estimator is fully robust; cluster standard errors (with T small).

- Or, can drop the d_{ir} and introduce mulitiplicative heterogeneity:

$$E(y_{it}|d_{iq},\ldots,d_{iT},c_i) = c_i \exp\left[\sum_{s=2}^{T}\theta_s fs_t + \sum_{r=q}^{T}\sum_{s=r}^{T}\tau_{rs}(w_{it}\cdot d_{ir}\cdot fs_t)\right].$$

- Estimate by FE Poisson.
  - Estimates are identical to POLS – as in linear case.

- No longer equivalent with covariates.
- Can estimate

$$E(y_{it}|d_{iq},\ldots,d_{iT},\mathbf{x}_i,c_i) = c_i\exp\Bigg[\sum_{s=2}^{T}\theta_s fs_t + \sum_{s=2}^{T}(fs_t\cdot\mathbf{x}_i)\boldsymbol{\pi}_s + \sum_{r=q}^{T}\sum_{s=r}^{T}\tau_{rs}(w_{it}\cdot d_{ir}\cdot fs_t) + \sum_{r=q}^{T}\sum_{s=r}^{T}(w_{it}\cdot d_{ir}\cdot fs_t\cdot\dot{\mathbf{x}}_{ir})\boldsymbol{\rho}_{rs}\Bigg]$$

by FE Poisson.

  - Fully robust, allows unbalanced panels.

• Underlying common trends assumption to identify ATTs:

$$\frac{E[y_t(0)|d_q,\ldots,d_T,\mathbf{x}]}{E[y_1(0)|d_q,\ldots,d_T,\mathbf{x}]} = \frac{E[y_t(0)|\mathbf{x}]}{E[y_1(0)|\mathbf{x}]}$$

• For other nonlinear response functions – logit, probit – CT assumption is on underlying latent variable.

6. Concluding Remarks

- Equivalence between TWFE and TWM has applications to event study estimators.
  - Show TWFE can be made much more flexible than constant effect.
  - TWFE some resilience to unbalanced panels.
  - TWFE can be used for exponential models.
  - TWM extends to general nonlinear models (logit, fractional logit).
- Equivalence may also suggest different strategies for factor models.

7. Stata Output: Staggered Case

```
. use staggered_6, clear

.
. xtset id year
       panel variable:  id (strongly balanced)
        time variable:  year, 2011 to 2016
                delta:  1 unit

. gen f2014 = year == 2014

. gen f2015 = year == 2015

. gen f2016 = year == 2016

. egen wsum = sum(w), by(id)

. gen d4 = wsum == 3

. gen d5 = wsum == 2

. gen d6 = wsum == 1
```

```
. * Constant TE:
.
. xtreg logy w f2014 f2015 f2016, fe vce(cluster id)

Fixed-effects (within) regression               Number of obs     =      3,270
Group variable: id                              Number of groups  =        545

R-sq:                                           Obs per group:
     within  = 0.1106                                         min =          6
     between = 0.0100                                         avg =        6.0
     overall = 0.0001                                         max =          6

                                                F(4,544)          =      77.56
corr(u_i, Xb)  = -0.0655                        Prob > F          =     0.0000

                                 (Std. Err. adjusted for 545 clusters in id)
------------------------------------------------------------------------------
             |               Robust
        logy |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           w |   .1633485   .0148916    10.97   0.000     .1340964    .1926007
       f2014 |    .067731    .010606     6.39   0.000     .0468972    .0885649
       f2015 |  -.0314376   .0109958    -2.86   0.004    -.0530371   -.0098381
       f2016 |    .061815   .0109547     5.64   0.000     .0402962    .0833337
       _cons |   2.412875   .0035134   686.77   0.000     2.405973    2.419776
-------------+----------------------------------------------------------------
     sigma_u |  .97499069
     sigma_e |  .19979414
         rho |  .95970045   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

```
. reg logy w f2014 f2015 f2016 d4 d5 d6, vce(cluster id)

Linear regression                               Number of obs     =      3,270
                                                F(7, 544)         =      46.52
                                                Prob > F          =     0.0000
                                                R-squared         =     0.0164
                                                Root MSE          =     .98206

                                  (Std. Err. adjusted for 545 clusters in id)
------------------------------------------------------------------------------
             |               Robust
        logy |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           w |   .1633485   .0148985    10.96   0.000     .1340829    .1926142
       f2014 |    .067731   .0106109     6.38   0.000     .0468876    .0885744
       f2015 |  -.0314376   .0110009    -2.86   0.004     -.053047   -.0098282
       f2016 |    .061815   .0109598     5.64   0.000     .0402863    .0833436
          d4 |  -.3287467   .0910431    -3.61   0.000    -.5075857   -.1499077
          d5 |  -.0187403   .2060319    -0.09   0.928    -.4234558    .3859753
          d6 |   .0190121   .2663328     0.07   0.943    -.5041546    .5421789
       _cons |   2.494212   .0521605    47.82   0.000     2.391751    2.596672
------------------------------------------------------------------------------
```

```
. * TE varies by period:
.
. xtreg logy c.w#c.f2014 c.w#c.f2015 c.w#c.f2016 ///
>         f2014 f2015 f2016, fe vce(cluster id)

                                   (Std. Err. adjusted for 545 clusters in id)
------------------------------------------------------------------------------
             |               Robust
        logy |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
 c.w#c.f2014 |   .1700551   .0220181     7.72   0.000     .1268043    .2133059
             |
 c.w#c.f2015 |   .1569093    .021125     7.43   0.000     .1154127     .198406
             |
 c.w#c.f2016 |   .1639358   .0221439     7.40   0.000     .1204379    .2074338
             |
       f2014 |   .0660821   .0114382     5.78   0.000     .0436136    .0885506
       f2015 |  -.0294763   .0118883    -2.48   0.013    -.0528288   -.0061237
       f2016 |   .0616178   .0119632     5.15   0.000     .0381181    .0851174
       _cons |   2.412875   .0035142   686.61   0.000     2.405972    2.419778
-------------+----------------------------------------------------------------
     sigma_u |  .97500299
     sigma_e |  .19985916
         rho |  .95967624   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

```
. reg logy c.w#c.f2014 c.w#c.f2015 c.w#c.f2016 ///
>         f2014 f2015 f2016 d4 d5 d6, vce(cluster id)

                                   (Std. Err. adjusted for 545 clusters in id)
------------------------------------------------------------------------------
             |               Robust
        logy |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
 c.w#c.f2014 |   .1700551   .0220282     7.72   0.000     .1267844    .2133258
             |
 c.w#c.f2015 |   .1569093   .0211348     7.42   0.000     .1153936    .1984251
             |
 c.w#c.f2016 |   .1639358    .022154     7.40   0.000     .1204179    .2074538
             |
       f2014 |   .0660821   .0114435     5.77   0.000     .0436032    .0885609
       f2015 |  -.0294763   .0118937    -2.48   0.014    -.0528396    -.006113
       f2016 |   .0616178   .0119687     5.15   0.000     .0381073    .0851283
          d4 |  -.3288891   .0910915    -3.61   0.000    -.5078233    -.149955
          d5 |   -.017765   .2060861    -0.09   0.931     -.422587     .387057
          d6 |   .0189143   .2664067     0.07   0.943    -.5043976    .5422262
       _cons |   2.494192   .0521756    47.80   0.000     2.391702    2.596683
------------------------------------------------------------------------------
```

```
. xtreg logy c.w#c.f2014 c.w#c.f2015 c.w#c.f2016 ///
>         f2014 f2015 f2016 d4 d5 d6, re vce(cluster id)

                                   (Std. Err. adjusted for 545 clusters in id)
------------------------------------------------------------------------------
             |               Robust
        logy |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
 c.w#c.f2014 |   .1700551   .0220282     7.72   0.000     .1268807    .2132296
             |
 c.w#c.f2015 |   .1569093   .0211348     7.42   0.000      .115486    .1983327
             |
 c.w#c.f2016 |   .1639358    .022154     7.40   0.000     .1205147     .207357
             |
       f2014 |   .0660821   .0114435     5.77   0.000     .0436532    .0885109
       f2015 |  -.0294763   .0118937    -2.48   0.013    -.0527876    -.006165
       f2016 |   .0616178   .0119687     5.15   0.000     .0381596     .085076
          d4 |  -.3288891   .0910915    -3.61   0.000    -.5074252   -.1503531
          d5 |   -.017765   .2060861    -0.09   0.931    -.4216863    .3861564
          d6 |   .0189143   .2664067     0.07   0.943    -.5032334    .5410619
       _cons |   2.494192   .0521756    47.80   0.000      2.39193    2.596455
-------------+----------------------------------------------------------------
     sigma_u |   .9638903
     sigma_e |  .19985916
         rho |  .95877965   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

```
. * TE varies by entry cohort (intensity):
.
. xtreg logy c.w#c.d4 c.w#c.d5 c.w#c.d6 ///
>         f2014 f2015 f2016, fe vce(cluster id)

                                   (Std. Err. adjusted for 545 clusters in id)
------------------------------------------------------------------------------
             |               Robust
        logy |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    c.w#c.d4 |   .1800497   .0163678    11.00   0.000      .147898    .2122015
             |
    c.w#c.d5 |   .1133156   .0314756     3.60   0.000     .0514869    .1751442
             |
    c.w#c.d6 |   .0919859   .0637986     1.44   0.150    -.0333359    .2173078
             |
       f2014 |   .0636247   .0107827     5.90   0.000     .0424438    .0848055
       f2015 |  -.0326062   .0110059    -2.96   0.003    -.0542254    -.010987
       f2016 |   .0628723   .0109928     5.72   0.000     .0412789    .0844658
       _cons |   2.412875   .0035181   685.84   0.000     2.405964    2.419786
-------------+----------------------------------------------------------------
     sigma_u |  .97563289
     sigma_e |  .19965948
         rho |   .9598034   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

```
. reg logy c.w#c.d4 c.w#c.d5 c.w#c.d6 ///
>         f2014 f2015 f2016 d4 d5 d6, vce(cluster id)

                                   (Std. Err. adjusted for 545 clusters in id)
------------------------------------------------------------------------------
             |               Robust
        logy |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    c.w#c.d4 |   .1800497   .0163753    11.00   0.000     .1478832    .2122163
             |
    c.w#c.d5 |   .1133156   .0314901     3.60   0.000     .0514584    .1751727
             |
    c.w#c.d6 |   .0919859    .063828     1.44   0.150    -.0333936    .2173654
             |
       f2014 |   .0636247   .0107877     5.90   0.000     .0424341    .0848153
       f2015 |  -.0326062   .0110109    -2.96   0.003    -.0542354    -.010977
       f2016 |   .0628723   .0109978     5.72   0.000     .0412689    .0844757
          d4 |  -.3370973   .0910864    -3.70   0.000    -.5160215   -.1581731
          d5 |  -.0020626   .2058754    -0.01   0.992    -.4064708    .4023456
          d6 |   .0309059   .2665283     0.12   0.908    -.4926449    .5544567
       _cons |   2.494915   .0521823    47.81   0.000     2.392411    2.597418
------------------------------------------------------------------------------
```

```
. xtreg logy c.w#c.d4 c.w#c.d5 c.w#c.d6 ///
>         f2014 f2015 f2016 d4 d5 d6, re vce(cluster id)

                                  (Std. Err. adjusted for 545 clusters in id)
------------------------------------------------------------------------------
             |               Robust
        logy |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    c.w#c.d4 |   .1800497   .0163753    11.00   0.000     .1479547    .2121447
             |
    c.w#c.d5 |   .1133156   .0314901     3.60   0.000     .0515961    .1750351
             |
    c.w#c.d6 |   .0919859    .063828     1.44   0.150    -.0331146    .2170865
             |
       f2014 |   .0636247   .0107877     5.90   0.000     .0424812    .0847681
       f2015 |  -.0326062   .0110109    -2.96   0.003    -.0541872   -.0110252
       f2016 |   .0628723   .0109978     5.72   0.000      .041317    .0844277
          d4 |  -.3370973   .0910864    -3.70   0.000    -.5156234   -.1585712
          d5 |  -.0020626   .2058754    -0.01   0.992    -.4055711    .4014458
          d6 |   .0309059   .2665283     0.12   0.908      -.49148    .5532919
       _cons |   2.494915   .0521823    47.81   0.000     2.392639     2.59719
-------------+----------------------------------------------------------------
     sigma_u |   .9638972
     sigma_e |  .19965948
         rho |  .95885915   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

```
. * TE varies by intensity (cohort) and calendar year:
.
. xtreg logy c.d4#c.f2014 c.d4#c.f2015 c.d4#c.f2016 ///
>         c.d5#c.f2015 c.d5#c.f2016 ///
>         c.d6#c.f2016 ///
>         f2014 f2015 f2016, fe vce(cluster id)

                                  (Std. Err. adjusted for 545 clusters in id)
------------------------------------------------------------------------------
             |               Robust
        logy |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
c.d4#c.f2014 |   .1799818   .0223482     8.05   0.000     .1360826    .2238811
             |
c.d4#c.f2015 |    .175937   .0228629     7.70   0.000     .1310266    .2208473
             |
c.d4#c.f2016 |   .1843389   .0249739     7.38   0.000     .1352819    .2333959
             |
c.d5#c.f2015 |   .0986968   .0411317     2.40   0.017     .0179005    .1794931
             |
c.d5#c.f2016 |   .1280679   .0439805     2.91   0.004     .0416755    .2144603
             |
c.d6#c.f2016 |   .0943579   .0640588     1.47   0.141     -.031475    .2201909
             |
       f2014 |   .0636414   .0114978     5.54   0.000     .0410559    .0862268
       f2015 |  -.0307366   .0118934    -2.58   0.010    -.0540993    -.007374
       f2016 |   .0608776   .0119708     5.09   0.000      .037363    .0843921
       _cons |   2.412875   .0035195   685.57   0.000     2.405961    2.419788
-------------+----------------------------------------------------------------
     sigma_u |  .97563252
     sigma_e |  .19975631
         rho |  .95976594   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

```
. reg logy c.d4#c.f2014 c.d4#c.f2015 c.d4#c.f2016 ///
>         c.d5#c.f2015 c.d5#c.f2016 ///
>         c.d6#c.f2016 ///
>         f2014 f2015 f2016 d4 d5 d6, vce(cluster id)

                                   (Std. Err. adjusted for 545 clusters in id)
------------------------------------------------------------------------------
             |               Robust
        logy |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
c.d4#c.f2014 |   .1799818   .0223584     8.05   0.000     .1360624    .2239013
             |
c.d4#c.f2015 |    .175937   .0228734     7.69   0.000      .131006     .220868
             |
c.d4#c.f2016 |   .1843389   .0249854     7.38   0.000     .1352593    .2334185
             |
c.d5#c.f2015 |   .0986968   .0411506     2.40   0.017     .0178633    .1795303
             |
c.d5#c.f2016 |   .1280679   .0440007     2.91   0.004     .0416357    .2145001
             |
c.d6#c.f2016 |   .0943579   .0640883     1.47   0.142    -.0315329    .2202488
             |
       f2014 |   .0636414   .0115031     5.53   0.000     .0410455    .0862372
       f2015 |  -.0307366   .0118989    -2.58   0.010    -.0541101   -.0073632
       f2016 |   .0608776   .0119763     5.08   0.000     .0373522     .084403
          d4 |  -.3371154   .0911247    -3.70   0.000    -.5161148    -.158116
          d5 |  -.0020849    .205955    -0.01   0.992    -.4066494    .4024797
          d6 |   .0305106   .2666447     0.11   0.909    -.4932688      .55429
       _cons |   2.494933   .0522037    47.79   0.000     2.392387    2.597478
------------------------------------------------------------------------------
```

```
. xtreg logy c.d4#c.f2014 c.d4#c.f2015 c.d4#c.f2016 ///
>         c.d5#c.f2015 c.d5#c.f2016 ///
>         c.d6#c.f2016 ///
>         f2014 f2015 f2016 d4 d5 d6, re vce(cluster id)

                                   (Std. Err. adjusted for 545 clusters in id)
------------------------------------------------------------------------------
             |               Robust
        logy |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
c.d4#c.f2014 |   .1799818   .0223584     8.05   0.000     .1361601    .2238036
             |
c.d4#c.f2015 |    .175937   .0228734     7.69   0.000     .1311059     .220768
             |
c.d4#c.f2016 |   .1843389   .0249854     7.38   0.000     .1353685    .2333093
             |
c.d5#c.f2015 |   .0986968   .0411506     2.40   0.016     .0180431    .1793505
             |
c.d5#c.f2016 |   .1280679   .0440007     2.91   0.004      .041828    .2143078
             |
c.d6#c.f2016 |   .0943579   .0640883     1.47   0.141    -.0312529    .2199687
             |
       f2014 |   .0636414   .0115031     5.53   0.000     .0410958     .086187
       f2015 |  -.0307366   .0118989    -2.58   0.010    -.0540581   -.0074152
       f2016 |   .0608776   .0119763     5.08   0.000     .0374045    .0843506
          d4 |  -.3371154   .0911247    -3.70   0.000    -.5157165   -.1585142
          d5 |  -.0020849    .205955    -0.01   0.992    -.4057493    .4015796
          d6 |   .0305106   .2666447     0.11   0.909    -.4921035    .5531247
       _cons |   2.494933   .0522037    47.79   0.000     2.392615     2.59725
-------------+----------------------------------------------------------------
     sigma_u |  .96389386
```

```
    sigma_e |  .19975631
        rho |   .9588206   (fraction of variance due to u_i)
------------------------------------------------------------------------------

. sum x1 if d4

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
          x1 |       804    11.73881    1.197314          8         15

. gen x1_dm4 = x1 - r(mean)

. sum x1 if d5

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
          x1 |       192    11.28125    1.529488          6         14

. gen x1_dm5 = x1 - r(mean)

. sum x1 if d6

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+--------------------------------------------------------
          x1 |       102          12    1.980099          9         15

. gen x1_dm6 = x1 - r(mean)
```

```
. xtreg logy c.w#c.d4#c.f2014 c.w#c.d4#c.f2015 c.w#c.d4#c.f2016 ///
>         c.w#c.d5#c.f2015 c.w#c.d5#c.f2016 ///
>         c.w#c.d6#c.f2016 ///
>         c.w#c.d4#c.f2014#c.x1_dm4 c.w#c.d4#c.f2015#c.x1_dm4 c.w#c.d4#c.f2016#c.x1_dm4 /
>         c.w#c.d5#c.f2015#c.x1_dm5 c.w#c.d5#c.f2016#c.x1_dm5 ///
>         c.w#c.d6#c.f2016#c.x1_dm6 ///
>         f2014 f2015 f2016 c.f2014#c.x1 c.f2015#c.x1 c.f2016#c.x1, fe vce(cluster id)

                                               (Std. Err. adjusted for 545 clusters in id
-------------------------------------------------------------------------------------------
                          |               Robust
                     logy |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval
--------------------------+----------------------------------------------------------------
          c.w#c.d4#c.f2014 |   .1800395   .0222895     8.08   0.000     .1362555    .2238236
                          |
          c.w#c.d4#c.f2015 |   .1758216   .0225127     7.81   0.000     .1315991     .220044
                          |
          c.w#c.d4#c.f2016 |   .1849706   .0249513     7.41   0.000     .1359579    .2339833
                          |
          c.w#c.d5#c.f2015 |   .0978163   .0413402     2.37   0.018     .0166103    .1790222
                          |
          c.w#c.d5#c.f2016 |   .1327046   .0434009     3.06   0.002     .0474506    .2179586
                          |
          c.w#c.d6#c.f2016 |    .092621    .062385     1.48   0.138    -.0299239    .2151659
                          |
c.w#c.d4#c.f2014#c.x1_dm4 |  -.0189186   .0161854    -1.17   0.243    -.0507122     .012875
                          |
c.w#c.d4#c.f2015#c.x1_dm4 |  -.0392521   .0176217    -2.23   0.026    -.0738671   -.0046372
                          |
c.w#c.d4#c.f2016#c.x1_dm4 |  -.0246808   .0215333    -1.15   0.252    -.0669795    .0176178
                          |
c.w#c.d5#c.f2015#c.x1_dm5 |   .0001442   .0237887     0.01   0.995    -.0465848    .0468732
                          |
```

```
c.w#c.d5#c.f2016#c.x1_dm5 |   -.039724   .0212825    -1.87   0.063    -.0815299    .0020819
                          |
c.w#c.d6#c.f2016#c.x1_dm6 |  -.0403321   .0322018    -1.25   0.211    -.1035872     .022923
                          |
                    f2014 |   .0454511   .0707414     0.64   0.521    -.0935088    .1844109
                    f2015 |  -.0158952   .0783568    -0.20   0.839    -.1698141    .1380238
                    f2016 |  -.0474077   .0795173    -0.60   0.551    -.2036063    .1087908
                          |
             c.f2014#c.x1 |   .0015447   .0060751     0.25   0.799    -.0103889    .0134783
                          |
             c.f2015#c.x1 |  -.0012545   .0065546    -0.19   0.848    -.0141299    .0116209
                          |
             c.f2016#c.x1 |   .0091707   .0066265     1.38   0.167    -.0038459    .0221874
                          |
                    _cons |   2.412875   .0035054   688.34   0.000     2.405989    2.419761
--------------------------+----------------------------------------------------------------
                  sigma_u |  .97594894
                  sigma_e |   .1996671
                      rho |  .95982544   (fraction of variance due to u_i)
-------------------------------------------------------------------------------------------
```

```
. reg logy c.w#c.d4#c.f2014 c.w#c.d4#c.f2015 c.w#c.d4#c.f2016 ///
>         c.w#c.d5#c.f2015 c.w#c.d5#c.f2016 ///
>         c.w#c.d6#c.f2016 ///
>         c.w#c.d4#c.f2014#c.x1_dm4 c.w#c.d4#c.f2015#c.x1_dm4 c.w#c.d4#c.f2016#c.x1_dm4 /
>         c.w#c.d5#c.f2015#c.x1_dm5 c.w#c.d5#c.f2016#c.x1_dm5 ///
>         c.w#c.d6#c.f2016#c.x1_dm6 ///
>         f2014 f2015 f2016 c.f2014#c.x1 c.f2015#c.x1 c.f2016#c.x1 ///
>         d4 d5 d6 x1 c.d4#c.x1 c.d5#c.x1 c.d6#c.x1, vce(cluster id)

                                              (Std. Err. adjusted for 545 clusters in id
------------------------------------------------------------------------------------------
                          |               Robust
                     logy |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval
--------------------------+---------------------------------------------------------------
         c.w#c.d4#c.f2014 |   .1800395   .0223136     8.07   0.000     .1362082    .2238708
                          |
         c.w#c.d4#c.f2015 |   .1758216    .022537     7.80   0.000     .1315514    .2200917
                          |
         c.w#c.d4#c.f2016 |   .1849706   .0249782     7.41   0.000     .1359051    .2340361
                          |
         c.w#c.d5#c.f2015 |   .0978163   .0413848     2.36   0.018     .0165227    .1791098
                          |
         c.w#c.d5#c.f2016 |   .1327046   .0434477     3.05   0.002     .0473587    .2180505
                          |
         c.w#c.d6#c.f2016 |    .092621   .0624522     1.48   0.139    -.0300561    .2152981
                          |
c.w#c.d4#c.f2014#c.x1_dm4 |  -.0189186   .0162029    -1.17   0.243    -.0507465    .0129092
                          |
c.w#c.d4#c.f2015#c.x1_dm4 |  -.0392521   .0176407    -2.23   0.026    -.0739044   -.0045999
                          |
c.w#c.d4#c.f2016#c.x1_dm4 |  -.0246808   .0215565    -1.14   0.253    -.0670251    .0176634
                          |
c.w#c.d5#c.f2015#c.x1_dm5 |   .0001442   .0238144     0.01   0.995    -.0466352    .0469236
```

c.w#c.d5#c.f2016#c.x1_dm5	-.039724	.0213054	-1.86	0.063	-.081575	.002127
c.w#c.d6#c.f2016#c.x1_dm6	-.0403321	.0322365	-1.25	0.211	-.1036554	.0229912
f2014	.0454511	.0708177	0.64	0.521	-.0936586	.1845608
f2015	-.0158952	.0784413	-0.20	0.839	-.1699801	.1381897
f2016	-.0474077	.079603	-0.60	0.552	-.2037747	.1089592
c.f2014#c.x1	.0015447	.0060817	0.25	0.800	-.0104018	.0134911
c.f2015#c.x1	-.0012545	.0065617	-0.19	0.848	-.0141438	.0116348
c.f2016#c.x1	.0091707	.0066336	1.38	0.167	-.0038599	.0222014
d4	-1.356329	.7810326	-1.74	0.083	-2.890538	.17788
d5	1.191999	1.144603	1.04	0.298	-1.056385	3.440383
d6	1.690494	1.679344	1.01	0.315	-1.6083	4.989288
x1	.0682135	.025351	2.69	0.007	.0184158	.1180113
c.d4#c.x1	.0872358	.0672249	1.30	0.195	-.0448164	.2192881
c.d5#c.x1	-.1026349	.1014854	-1.01	0.312	-.3019862	.0967163
c.d6#c.x1	-.1394164	.1293121	-1.08	0.281	-.3934286	.1145958
_cons	1.689357	.3034252	5.57	0.000	1.093328	2.285385

```
. xtreg logy c.w#c.d4#c.f2014 c.w#c.d4#c.f2015 c.w#c.d4#c.f2016 ///
>         c.w#c.d5#c.f2015 c.w#c.d5#c.f2016 ///
>         c.w#c.d6#c.f2016 ///
>         c.w#c.d4#c.f2014#c.x1_dm4 c.w#c.d4#c.f2015#c.x1_dm4 c.w#c.d4#c.f2016#c.x1_dm4 /
>         c.w#c.d5#c.f2015#c.x1_dm5 c.w#c.d5#c.f2016#c.x1_dm5 ///
>         c.w#c.d6#c.f2016#c.x1_dm6 ///
>         f2014 f2015 f2016 c.f2014#c.x1 c.f2015#c.x1 c.f2016#c.x1 ///
>         d4 d5 d6 x1 c.d4#c.x1 c.d5#c.x1 c.d6#c.x1, re vce(cluster id)

                                                (Std. Err. adjusted for 545 clusters in id
-------------------------------------------------------------------------------------------
                          |               Robust
                     logy |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval
--------------------------+----------------------------------------------------------------
         c.w#c.d4#c.f2014 |   .1800395   .0223136     8.07   0.000     .1363058    .2237733
                          |
         c.w#c.d4#c.f2015 |   .1758216    .022537     7.80   0.000     .1316499    .2199932
                          |
         c.w#c.d4#c.f2016 |   .1849706   .0249782     7.41   0.000     .1360143     .233927
                          |
         c.w#c.d5#c.f2015 |   .0978163   .0413848     2.36   0.018     .0167036    .1789289
                          |
         c.w#c.d5#c.f2016 |   .1327046   .0434477     3.05   0.002     .0475486    .2178606
                          |
         c.w#c.d6#c.f2016 |    .092621   .0624522     1.48   0.138    -.0297831    .2150251
                          |
c.w#c.d4#c.f2014#c.x1_dm4 |  -.0189186   .0162029    -1.17   0.243    -.0506757    .0128384
                          |
c.w#c.d4#c.f2015#c.x1_dm4 |  -.0392521   .0176407    -2.23   0.026    -.0738273   -.004677
                          |
c.w#c.d4#c.f2016#c.x1_dm4 |  -.0246808   .0215565    -1.14   0.252    -.0669309    .0175692
                          |
c.w#c.d5#c.f2015#c.x1_dm5 |   .0001442   .0238144     0.01   0.995    -.0465311    .0468195
```

c.w#c.d5#c.f2016#c.x1_dm5	-.039724	.0213054	-1.86	0.062	-.0814819	.0020339
c.w#c.d6#c.f2016#c.x1_dm6	-.0403321	.0322365	-1.25	0.211	-.1035145	.0228503
f2014	.0454511	.0708177	0.64	0.521	-.0933491	.1842513
f2015	-.0158952	.0784413	-0.20	0.839	-.1696373	.1378469
f2016	-.0474077	.079603	-0.60	0.551	-.2034268	.1086113
c.f2014#c.x1	.0015447	.0060817	0.25	0.800	-.0103752	.0134646
c.f2015#c.x1	-.0012545	.0065617	-0.19	0.848	-.0141151	.0116062
c.f2016#c.x1	.0091707	.0066336	1.38	0.167	-.003831	.0221724
d4	-1.356329	.7810326	-1.74	0.082	-2.887125	.1744666
d5	1.191999	1.144603	1.04	0.298	-1.051383	3.43538
d6	1.690494	1.679344	1.01	0.314	-1.60096	4.981949
x1	.0682135	.025351	2.69	0.007	.0185266	.1179005
c.d4#c.x1	.0872358	.0672249	1.30	0.194	-.0445226	.2189943
c.d5#c.x1	-.1026349	.1014854	-1.01	0.312	-.3015426	.0962728
c.d6#c.x1	-.1394164	.1293121	-1.08	0.281	-.3928634	.1140306
_cons	1.689357	.3034252	5.57	0.000	1.094654	2.284059
sigma_u	.95699311					
sigma_e	.1996671					
rho	.9582852	(fraction of variance due to u_i)				

```
. * Now use margins for ATTs to account for sampling error in the covariate means.
. * The changes in standard errors tend to be minor:
.
. reg logy c.w#c.d4#c.f2014 c.w#c.d4#c.f2015 c.w#c.d4#c.f2016 ///
>         c.w#c.d5#c.f2015 c.w#c.d5#c.f2016 ///
>         c.w#c.d6#c.f2016 ///
>         c.w#c.d4#c.f2014#c.x1 c.w#c.d4#c.f2015#c.x1 c.w#c.d4#c.f2016#c.x1 ///
>         c.w#c.d5#c.f2015#c.x1 c.w#c.d5#c.f2016#c.x1 ///
>         c.w#c.d6#c.f2016#c.x1 ///
>         f2014 f2015 f2016 c.f2014#c.x1 c.f2015#c.x1 c.f2016#c.x1 ///
>         d4 d5 d6 x1 c.d4#c.x1 c.d5#c.x1 c.d6#c.x1, vce(cluster id)

                                              (Std. Err. adjusted for 545 clusters in id)
---------------------------------------------------------------------------------------
                      |               Robust
                 logy |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
----------------------+----------------------------------------------------------------
     c.w#c.d4#c.f2014 |   .4021219   .1899911     2.12   0.035     .0289157     .775328
                      |
     c.w#c.d4#c.f2015 |   .6365949   .2113629     3.01   0.003     .2214076    1.051782
                      |
     c.w#c.d4#c.f2016 |   .4746943   .2530328     1.88   0.061    -.0223467    .9717353
                      |
     c.w#c.d5#c.f2015 |   .0961897   .2600982     0.37   0.712    -.4147302    .6071095
                      |
     c.w#c.d5#c.f2016 |   .5808412   .2470379     2.35   0.019     .0955762    1.066106
                      |
     c.w#c.d6#c.f2016 |   .5766064   .3640648     1.58   0.114    -.1385386    1.291751
                      |
c.w#c.d4#c.f2014#c.x1 |  -.0189186   .0162029    -1.17   0.243    -.0507465    .0129092
                      |
c.w#c.d4#c.f2015#c.x1 |  -.0392521   .0176407    -2.23   0.026    -.0739044   -.0045999
```

c.w#c.d4#c.f2016#c.x1	-.0246808	.0215565	-1.14	0.253	-.0670251	.0176634
c.w#c.d5#c.f2015#c.x1	.0001442	.0238144	0.01	0.995	-.0466352	.0469236
c.w#c.d5#c.f2016#c.x1	-.039724	.0213054	-1.86	0.063	-.081575	.002127
c.w#c.d6#c.f2016#c.x1	-.0403321	.0322365	-1.25	0.211	-.1036554	.0229912
f2014	.0454511	.0708177	0.64	0.521	-.0936586	.1845607
f2015	-.0158952	.0784413	-0.20	0.839	-.1699801	.1381897
f2016	-.0474077	.079603	-0.60	0.552	-.2037747	.1089592
c.f2014#c.x1	.0015447	.0060817	0.25	0.800	-.0104018	.0134911
c.f2015#c.x1	-.0012545	.0065617	-0.19	0.848	-.0141438	.0116348
c.f2016#c.x1	.0091707	.0066336	1.38	0.167	-.0038599	.0222014
d4	-1.356329	.7810326	-1.74	0.083	-2.890538	.17788
d5	1.191999	1.144603	1.04	0.298	-1.056385	3.440383
d6	1.690494	1.679344	1.01	0.315	-1.6083	4.989288
x1	.0682135	.025351	2.69	0.007	.0184158	.1180113
c.d4#c.x1	.0872358	.0672249	1.30	0.195	-.0448164	.2192881
c.d5#c.x1	-.1026349	.1014854	-1.01	0.312	-.3019862	.0967163
c.d6#c.x1	-.1394164	.1293121	-1.08	0.281	-.3934286	.1145958
_cons	1.689357	.3034252	5.57	0.000	1.093328	2.285385

.

```
. margins, dydx(w) at(d4 = 1 d5 = 0 d6 = 0 f2014 = 1 f2015 = 0 f2016 = 0) ///
>         subpop(if d4 == 1) vce(uncond)

Average marginal effects                        Number of obs     =      3,270
                                                Subpop. no. obs   =        804

Expression   : Linear prediction, predict()
dy/dx w.r.t. : w
at           : d4              =           1
               f2014           =           1
               f2015           =           0
               f2016           =           0
               d5              =           0
               d6              =           0

                                   (Std. Err. adjusted for 545 clusters in id)
------------------------------------------------------------------------------
             |            Unconditional
             |      dy/dx   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           w |   .1800395   .0223999     8.04   0.000     .1360386    .2240404
------------------------------------------------------------------------------

. margins, dydx(w) at(d4 = 1 d5 = 0 d6 = 0 f2014 = 0 f2015 = 1 f2016 = 0) ///
>         subpop(if d4 == 1) vce(uncond)

Average marginal effects                        Number of obs     =      3,270
                                                Subpop. no. obs   =        804

Expression   : Linear prediction, predict()
dy/dx w.r.t. : w
at           : d4              =           1
               f2014           =           0
```

```
               f2015          =           1
               f2016          =           0
               d5             =           0
               d6             =           0

                                    (Std. Err. adjusted for 545 clusters in id)
------------------------------------------------------------------------------
             |            Unconditional
             |      dy/dx   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           w |   .1758216   .0229027     7.68   0.000     .1308329    .2208102
------------------------------------------------------------------------------

. margins, dydx(w) at(d4 = 1 d5 = 0 d6 = 0 f2014 = 0 f2015 = 0 f2016 = 1) ///
>         subpop(if d4 == 1) vce(uncond)

Average marginal effects                        Number of obs     =      3,270
                                                Subpop. no. obs   =        804

Expression   : Linear prediction, predict()
dy/dx w.r.t. : w
at           : d4             =           1
               f2014          =           0
               f2015          =           0
               f2016          =           1
               d5             =           0
               d6             =           0

                                    (Std. Err. adjusted for 545 clusters in id)
------------------------------------------------------------------------------
             |            Unconditional
             |      dy/dx   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
```

```
           w |   .1849706   .0251094     7.37   0.000     .1356474    .2342938
------------------------------------------------------------------------------

. margins, dydx(w) at(d4 = 0 d5 = 1 d6 = 0 f2014 = 0 f2015 = 1 f2016 = 0) ///
>          subpop(if d5 == 1) vce(uncond)

Average marginal effects                        Number of obs     =      3,270
                                                Subpop. no. obs   =        192

Expression   : Linear prediction, predict()
dy/dx w.r.t. : w
at           : d4              =           0
               f2014           =           0
               f2015           =           1
               f2016           =           0
               d5              =           1
               d6              =           0

                                   (Std. Err. adjusted for 545 clusters in id)
------------------------------------------------------------------------------
             |            Unconditional
             |      dy/dx   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           w |   .0978163   .0413848     2.36   0.018     .0165227    .1791098
------------------------------------------------------------------------------

. margins, dydx(w) at(d4 = 0 d5 = 1 d6 = 0 f2014 = 0 f2015 = 0 f2016 = 1) ///
>          subpop(if d5 == 1) vce(uncond)

Average marginal effects                        Number of obs     =      3,270
                                                Subpop. no. obs   =        192

Expression   : Linear prediction, predict()
```

```
dy/dx w.r.t. : w
at           : d4              =           0
               f2014           =           0
               f2015           =           0
               f2016           =           1
               d5              =           1
               d6              =           0

                                   (Std. Err. adjusted for 545 clusters in id)
------------------------------------------------------------------------------
             |            Unconditional
             |      dy/dx   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           w |   .1327046   .0447612     2.96   0.003     .0447787    .2206305
------------------------------------------------------------------------------

. margins, dydx(w) at(d4 = 0 d5 = 0 d6 = 1 f2014 = 0 f2015 = 0 f2016 = 1) ///
>         subpop(if d6 == 1) vce(uncond)

Average marginal effects                        Number of obs     =      3,270
                                                Subpop. no. obs   =        102

Expression   : Linear prediction, predict()
dy/dx w.r.t. : w
at           : d4              =           0
               f2014           =           0
               f2015           =           0
               f2016           =           1
               d5              =           0
               d6              =           1

                                   (Std. Err. adjusted for 545 clusters in id)
------------------------------------------------------------------------------
```

```
             |            Unconditional
             |      dy/dx   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           w |    .092621    .065386     1.42   0.157    -.0358189    .2210609
------------------------------------------------------------------------------
```

```
. * Now exponential model for y. Without covariates, FE Poisson and
. * pooled Poisson are identical. Adding the full set of year dummies
. * does not change the estimates.
.
. xtpoisson y c.d4#c.f2014 c.d4#c.f2015 c.d4#c.f2016 ///
>         c.d5#c.f2015 c.d5#c.f2016 ///
>         c.d6#c.f2016 ///
>         f2014 f2015 f2016, fe vce(robust)
note: you are responsible for interpretation of non-count dep. variable

                                     (Std. Err. adjusted for clustering on id)
------------------------------------------------------------------------------
             |               Robust
           y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
c.d4#c.f2014 |   .1942707   .0320979     6.05   0.000     .1313599    .2571814
             |
c.d4#c.f2015 |   .1708469   .0339736     5.03   0.000     .1042598     .237434
             |
c.d4#c.f2016 |   .2224609   .0299002     7.44   0.000     .1638575    .2810643
             |
c.d5#c.f2015 |   .0589306   .0440037     1.34   0.180    -.0273152    .1451763
             |
c.d5#c.f2016 |   .2043645   .0548574     3.73   0.000     .0968459    .3118831
             |
c.d6#c.f2016 |   .1179841   .1654163     0.71   0.476    -.2062258    .4421941
             |
       f2014 |    .045545   .0198769     2.29   0.022      .006587     .084503
       f2015 |  -.0547305   .0170008    -3.22   0.001    -.0880515   -.0214096
       f2016 |    .040442   .0188927     2.14   0.032     .0034131     .077471
------------------------------------------------------------------------------
```

```
. poisson y c.d4#c.f2014 c.d4#c.f2015 c.d4#c.f2016 ///
>         c.d5#c.f2015 c.d5#c.f2016 ///
>         c.d6#c.f2016 ///
>         f2014 f2015 f2016 d4 d5 d6, vce(cluster id)
note: you are responsible for interpretation of noncount dep. variable

                                   (Std. Err. adjusted for 545 clusters in id)
------------------------------------------------------------------------------
             |               Robust
           y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
c.d4#c.f2014 |   .1942707   .0321274     6.05   0.000     .1313022    .2572392
             |
c.d4#c.f2015 |   .1708469   .0340048     5.02   0.000     .1041986    .2374952
             |
c.d4#c.f2016 |   .2224609   .0299277     7.43   0.000     .1638036    .2811181
             |
c.d5#c.f2015 |   .0589306   .0440442     1.34   0.181    -.0273944    .1452556
             |
c.d5#c.f2016 |   .2043645   .0549078     3.72   0.000     .0967471    .3119818
             |
c.d6#c.f2016 |   .1179841   .1655683     0.71   0.476    -.2065237    .4424919
             |
       f2014 |    .045545   .0198951     2.29   0.022     .0065512    .0845388
       f2015 |  -.0547305   .0170164    -3.22   0.001    -.0880821    -.021379
       f2016 |    .040442     .01891     2.14   0.032      .003379     .077505
          d4 |  -.4453415   .1198097    -3.72   0.000    -.6801642   -.2105188
          d5 |   .0809309    .201272     0.40   0.688     -.313555    .4754169
          d6 |   .2727917   .3909351     0.70   0.485     -.493427     1.03901
       _cons |   3.000529   .0623774    48.10   0.000     2.878272    3.122787
------------------------------------------------------------------------------
```

```
. xtpoisson y c.d4#c.f2014 c.d4#c.f2015 c.d4#c.f2016 ///
>         c.d5#c.f2015 c.d5#c.f2016 ///
>         c.d6#c.f2016 ///
>         i.year, fe vce(robust)
note: you are responsible for interpretation of non-count dep. variable

                                     (Std. Err. adjusted for clustering on id)
------------------------------------------------------------------------------
             |               Robust
           y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
c.d4#c.f2014 |   .1942707   .0320979     6.05   0.000     .1313599    .2571814
             |
c.d4#c.f2015 |   .1708469   .0339736     5.03   0.000     .1042598     .237434
             |
c.d4#c.f2016 |   .2224609   .0299002     7.44   0.000     .1638575    .2810643
             |
c.d5#c.f2015 |   .0589306   .0440037     1.34   0.180    -.0273152    .1451763
             |
c.d5#c.f2016 |   .2043645   .0548574     3.73   0.000     .0968459    .3118831
             |
c.d6#c.f2016 |   .1179841   .1654163     0.71   0.476    -.2062258    .4421941
             |
        year |
       2012  |   .0306881   .0156213     1.96   0.049      .000071    .0613052
       2013  |   .0580666   .0168517     3.45   0.001     .0250379    .0910953
       2014  |    .075411   .0206204     3.66   0.000     .0349958    .1158263
       2015  |  -.0248645   .0203301    -1.22   0.221    -.0647108    .0149818
       2016  |    .070308   .0187326     3.75   0.000     .0335928    .1070233
------------------------------------------------------------------------------
```

```
. * Now with a covariate. The results are not the same, but the differences
. * in the estimated ATTs are minor in this application.
. * Also, the results change with full time dummies and full
. * of time dummy interactions with covariates.
.
. xtpoisson y c.w#c.d4#c.f2014 c.w#c.d4#c.f2015 c.w#c.d4#c.f2016 ///
>         c.w#c.d5#c.f2015 c.w#c.d5#c.f2016 ///
>         c.w#c.d6#c.f2016 ///
>         c.w#c.d4#c.f2014#c.x1_dm4 c.w#c.d4#c.f2015#c.x1_dm4 c.w#c.d4#c.f2016#c.x1_dm4 /
>         c.w#c.d5#c.f2015#c.x1_dm5 c.w#c.d5#c.f2016#c.x1_dm5 ///
>         c.w#c.d6#c.f2016#c.x1_dm6 ///
>         f2014 f2015 f2016 c.f2014#c.x1 c.f2015#c.x1 c.f2016#c.x1, fe vce(robust)
note: you are responsible for interpretation of non-count dep. variable

                                                  (Std. Err. adjusted for clustering on id
------------------------------------------------------------------------------
                          |               Robust
                        y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval
--------------------------+---------------------------------------------------
         c.w#c.d4#c.f2014 |   .1966912   .0320517     6.14   0.000     .1338709    .2595114
                          |
         c.w#c.d4#c.f2015 |    .181199   .0330198     5.49   0.000     .1164814    .2459165
                          |
         c.w#c.d4#c.f2016 |   .2307054   .0297962     7.74   0.000      .172306    .2891048
                          |
         c.w#c.d5#c.f2015 |   .0550393   .0431379     1.28   0.202    -.0295093     .139588
                          |
         c.w#c.d5#c.f2016 |   .2142023   .0527788     4.06   0.000     .1107577    .3176469
                          |
         c.w#c.d6#c.f2016 |   .0219704   .1270021     0.17   0.863    -.2269492      .27089
                          |
c.w#c.d4#c.f2014#c.x1_dm4 |   -.012003   .0214177    -0.56   0.575    -.0539809    .0299749
```

c.w#c.d4#c.f2015#c.x1_dm4	-.0602142	.0202287	-2.98	0.003	-.0998616	-.0205667
c.w#c.d4#c.f2016#c.x1_dm4	-.0347854	.029333	-1.19	0.236	-.0922771	.0227062
c.w#c.d5#c.f2015#c.x1_dm5	-.0194663	.0249223	-0.78	0.435	-.0683132	.0293806
c.w#c.d5#c.f2016#c.x1_dm5	-.0460565	.0245187	-1.88	0.060	-.0941123	.0019993
c.w#c.d6#c.f2016#c.x1_dm6	-.1263765	.0500253	-2.53	0.012	-.2244244	-.0283287
f2014	.041844	.1302967	0.32	0.748	-.2135328	.2972208
f2015	-.001671	.1172639	-0.01	0.989	-.231504	.2281621
f2016	-.1416546	.117782	-1.20	0.229	-.372503	.0891939
c.f2014#c.x1	.0003109	.0107946	0.03	0.977	-.0208461	.0214678
c.f2015#c.x1	-.0044377	.009647	-0.46	0.646	-.0233455	.01447
c.f2016#c.x1	.0151421	.0094951	1.59	0.111	-.0034679	.0337521

```
. poisson y c.w#c.d4#c.f2014 c.w#c.d4#c.f2015 c.w#c.d4#c.f2016 ///
>         c.w#c.d5#c.f2015 c.w#c.d5#c.f2016 ///
>         c.w#c.d6#c.f2016 ///
>         c.w#c.d4#c.f2014#c.x1_dm4 c.w#c.d4#c.f2015#c.x1_dm4 c.w#c.d4#c.f2016#c.x1_dm4 /
>         c.w#c.d5#c.f2015#c.x1_dm5 c.w#c.d5#c.f2016#c.x1_dm5 ///
>         c.w#c.d6#c.f2016#c.x1_dm6 ///
>         f2014 f2015 f2016 c.f2014#c.x1 c.f2015#c.x1 c.f2016#c.x1 ///
>         d4 d5 d6 x1 c.d4#c.x1 c.d5#c.x1 c.d6#c.x1, vce(cluster id)
note: you are responsible for interpretation of noncount dep. variable

                                                (Std. Err. adjusted for 545 clusters in id
------------------------------------------------------------------------------------------
                          |               Robust
                        y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval
--------------------------+---------------------------------------------------------------
         c.w#c.d4#c.f2014 |   .1960423   .0321189     6.10   0.000     .1330905    .2589942
                          |
         c.w#c.d4#c.f2015 |   .1782379   .0335015     5.32   0.000     .1125762    .2438995
                          |
         c.w#c.d4#c.f2016 |   .2291282   .0297649     7.70   0.000     .1707902    .2874663
                          |
         c.w#c.d5#c.f2015 |   .0552965   .0429822     1.29   0.198    -.0289471    .1395402
                          |
         c.w#c.d5#c.f2016 |   .2127154   .0526125     4.04   0.000     .1095968    .3158339
                          |
         c.w#c.d6#c.f2016 |   .0250988   .1058216     0.24   0.813    -.1823077    .2325053
                          |
c.w#c.d4#c.f2014#c.x1_dm4 |  -.0087947   .0166791    -0.53   0.598    -.0414852    .0238957
                          |
c.w#c.d4#c.f2015#c.x1_dm4 |   -.043178    .017645    -2.45   0.014    -.0777615   -.0085944
                          |
c.w#c.d4#c.f2016#c.x1_dm4 |  -.0276426   .0224272    -1.23   0.218    -.0715992    .0163139
                          |
```

c.w#c.d5#c.f2015#c.x1_dm5	-.0226903	.0298553	-0.76	0.447	-.0812055	.035825
c.w#c.d5#c.f2016#c.x1_dm5	-.0476805	.0244321	-1.95	0.051	-.0955665	.0002055
c.w#c.d6#c.f2016#c.x1_dm6	-.1207353	.0572943	-2.11	0.035	-.2330301	-.0084405
f2014	.0422137	.117699	0.36	0.720	-.1884721	.2728996
f2015	-.0077869	.1054262	-0.07	0.941	-.2144186	.1988447
f2016	-.1199528	.1051667	-1.14	0.254	-.3260757	.08617
c.f2014#c.x1	.0002798	.0097223	0.03	0.977	-.0187755	.0193351
c.f2015#c.x1	-.0039262	.0086462	-0.45	0.650	-.0208726	.0130201
c.f2016#c.x1	.0133375	.0084839	1.57	0.116	-.0032906	.0299656
d4	-1.525272	.6487306	-2.35	0.019	-2.79676	-.2537829
d5	.751651	.9702689	0.77	0.439	-1.150041	2.653343
d6	3.010725	1.848229	1.63	0.103	-.6117372	6.633187
x1	.0549107	.026275	2.09	0.037	.0034127	.1064087
c.d4#c.x1	.0914792	.0539856	1.69	0.090	-.0143307	.1972891
c.d5#c.x1	-.0564077	.0864516	-0.65	0.514	-.2258498	.1130344
c.d6#c.x1	-.2337497	.1524969	-1.53	0.125	-.532638	.0651387
_cons	2.34674	.3263905	7.19	0.000	1.707027	2.986454