

# Autocorrelation

EC 421, Set 8

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19 February 2019

# Prologue

# Schedule

## Last Time

Midterm + Introduction to time series + Autocorrelation

## Today

Autocorrelation

## Upcoming

- **Assignment** This week
- No office hours today.

# R showcase

## ggplot2

I previously mentioned the R package `ggplot2`.

Today, I'm going to show you a bit of the basics of `ggplot2`.

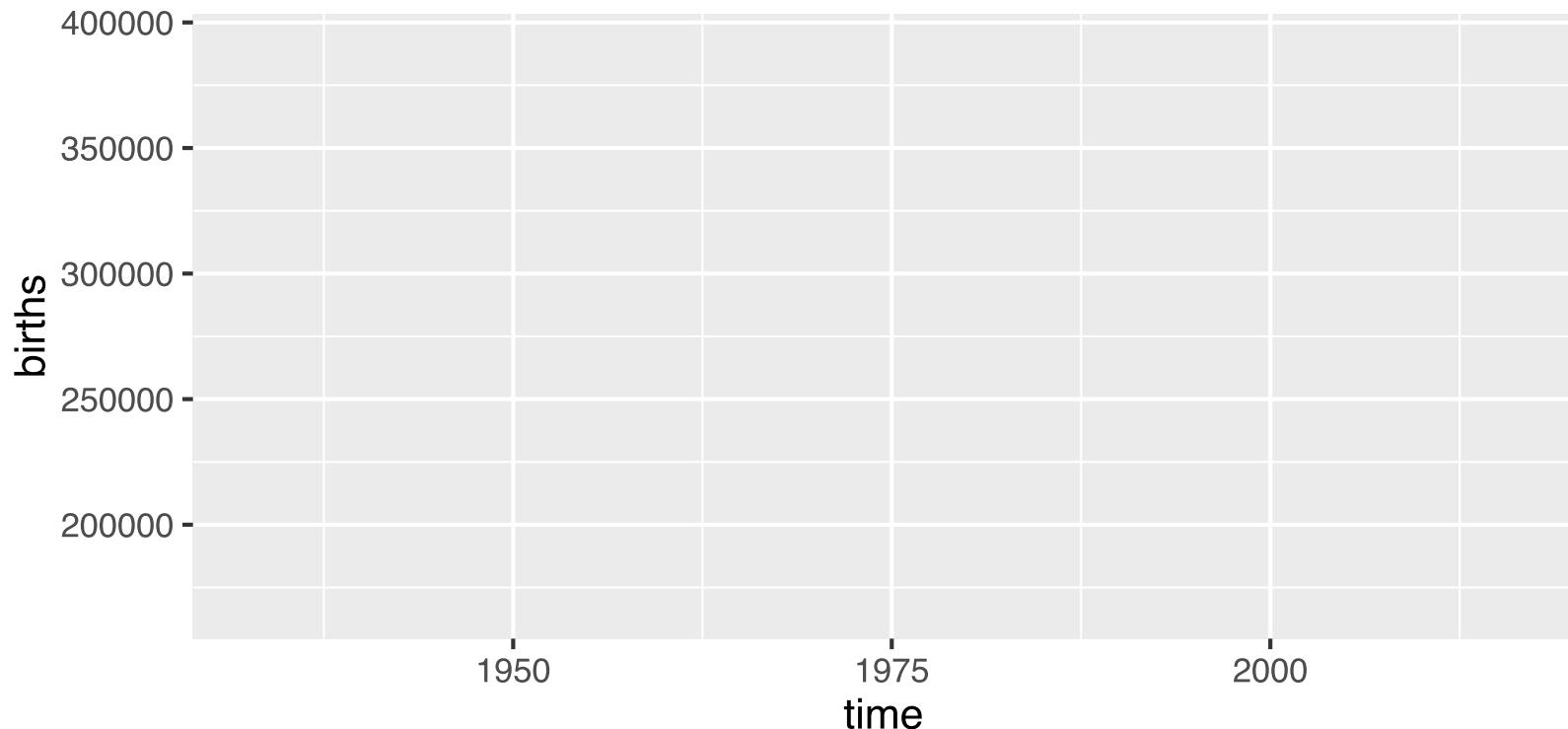
## Functions

I'm also going to tell you a bit about writing your own functions.

# ggplot2

The `ggplot` function `aes` arguments define variables from `data`.

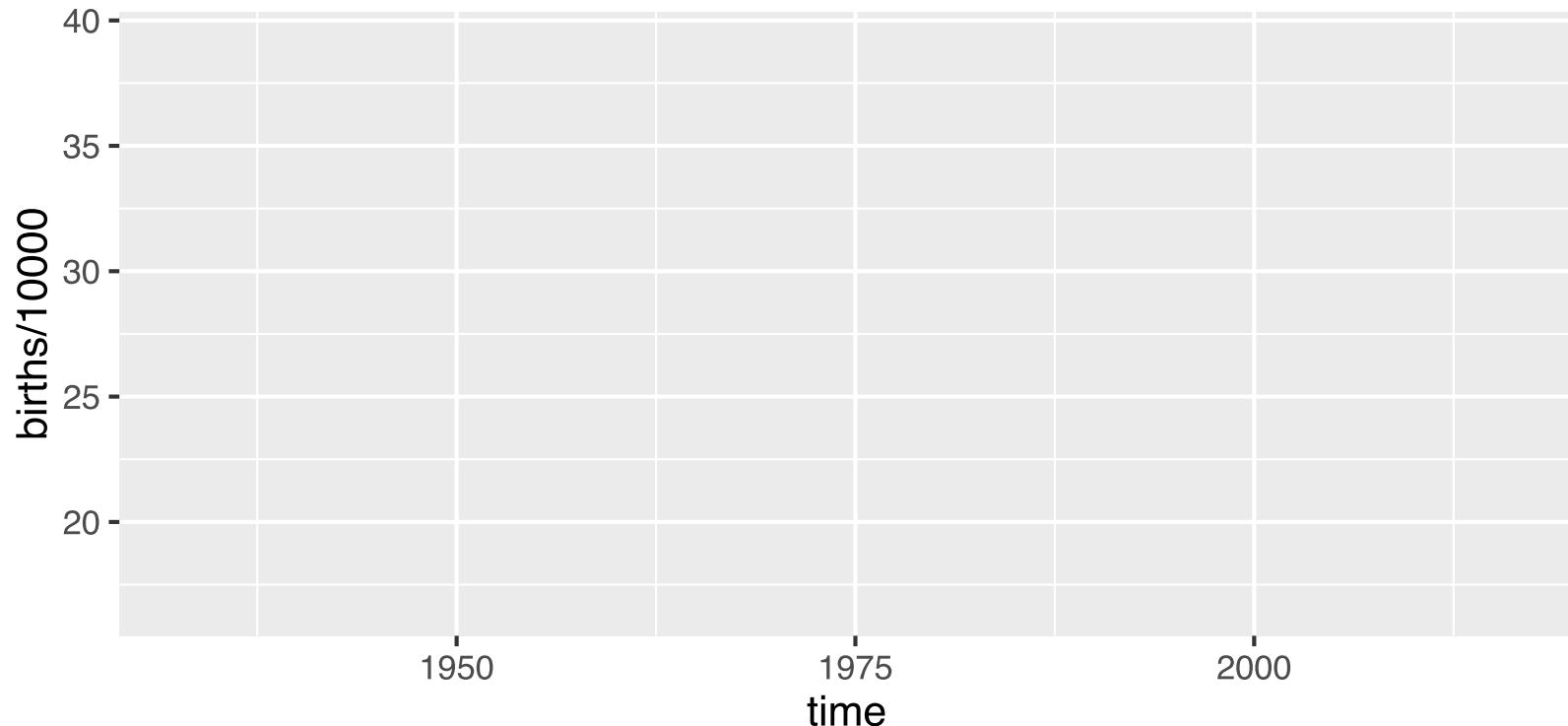
```
ggplot(data = birth_df, aes(x = time, y = births))
```



# ggplot2

You can apply mathematical operators to the variables.

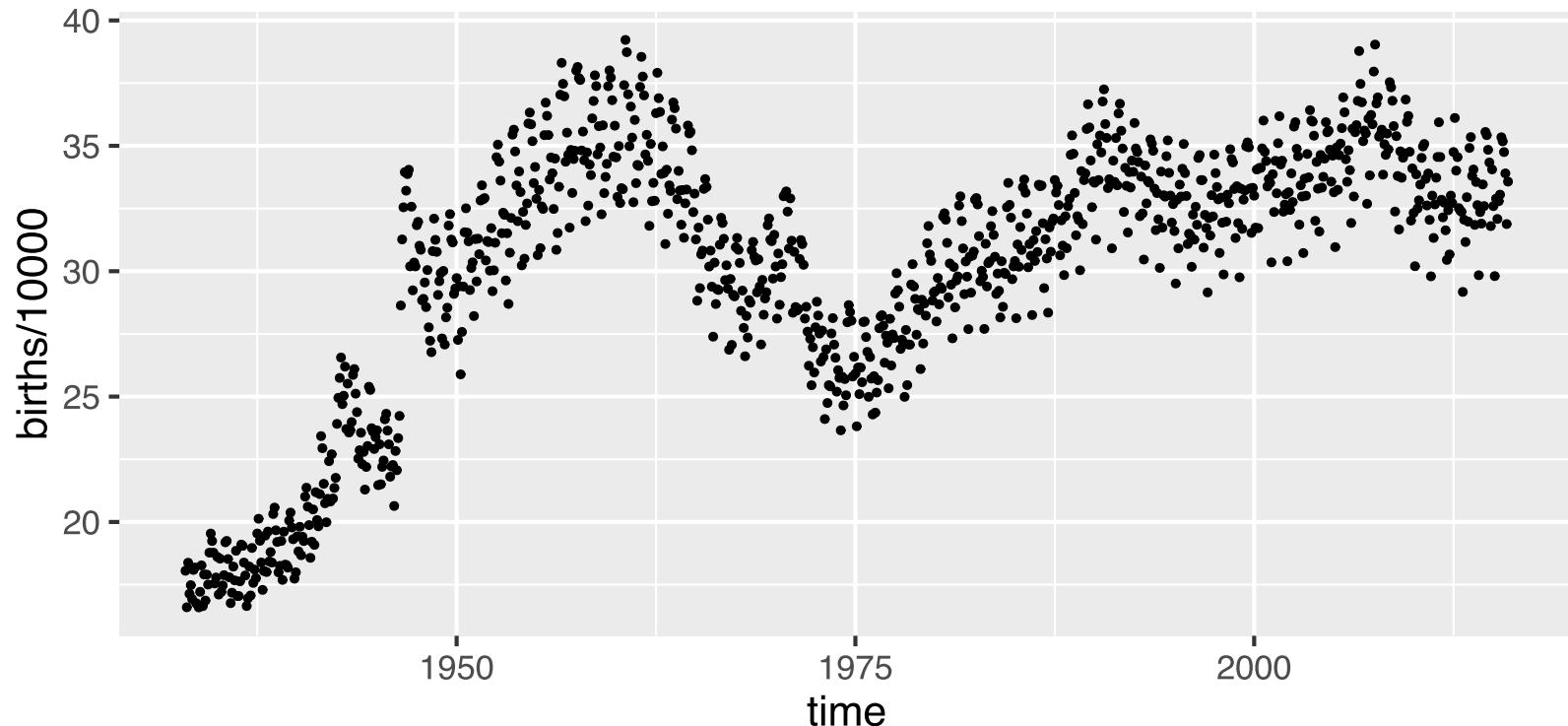
```
ggplot(data = birth_df, aes(x = time, y = births/10000))
```



# ggplot2

You add *geometries* (points, lines, etc.) layer by layer.

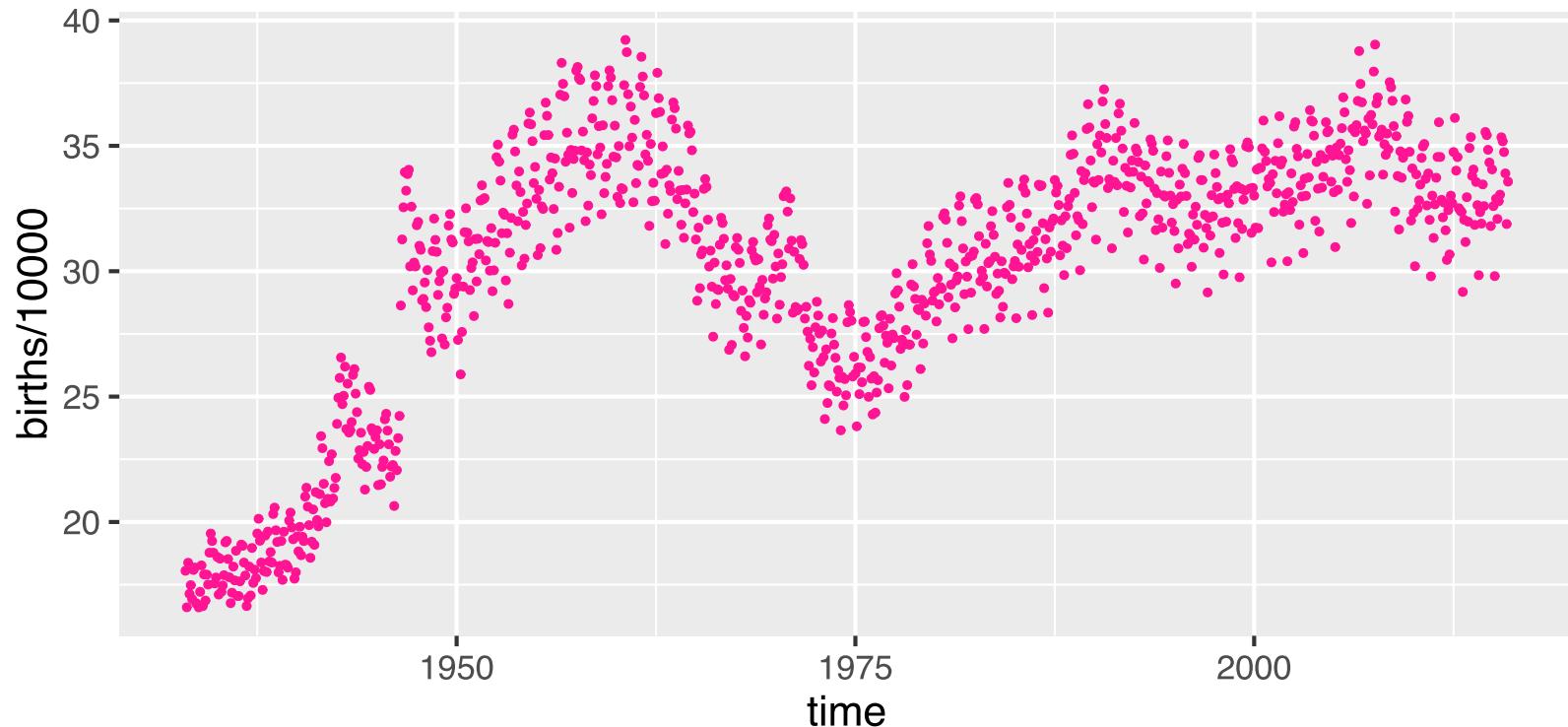
```
ggplot(data = birth_df, aes(x = time, y = births/10000)) +  
  geom_point()
```



# ggplot2

Color is easy.

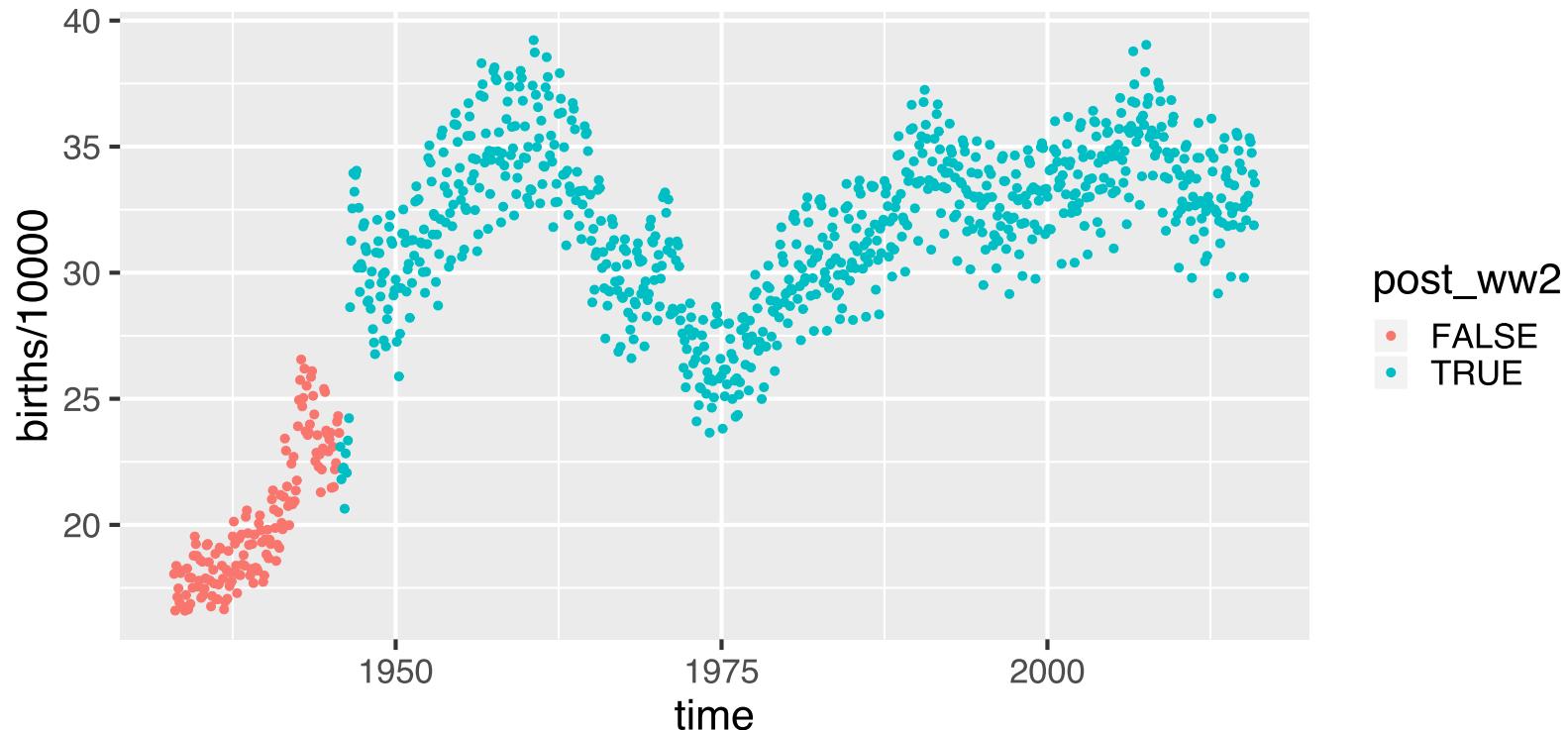
```
ggplot(data = birth_df, aes(x = time, y = births/10000)) +  
  geom_point(color = "deeppink")
```



# ggplot2

You can even use variables to color.

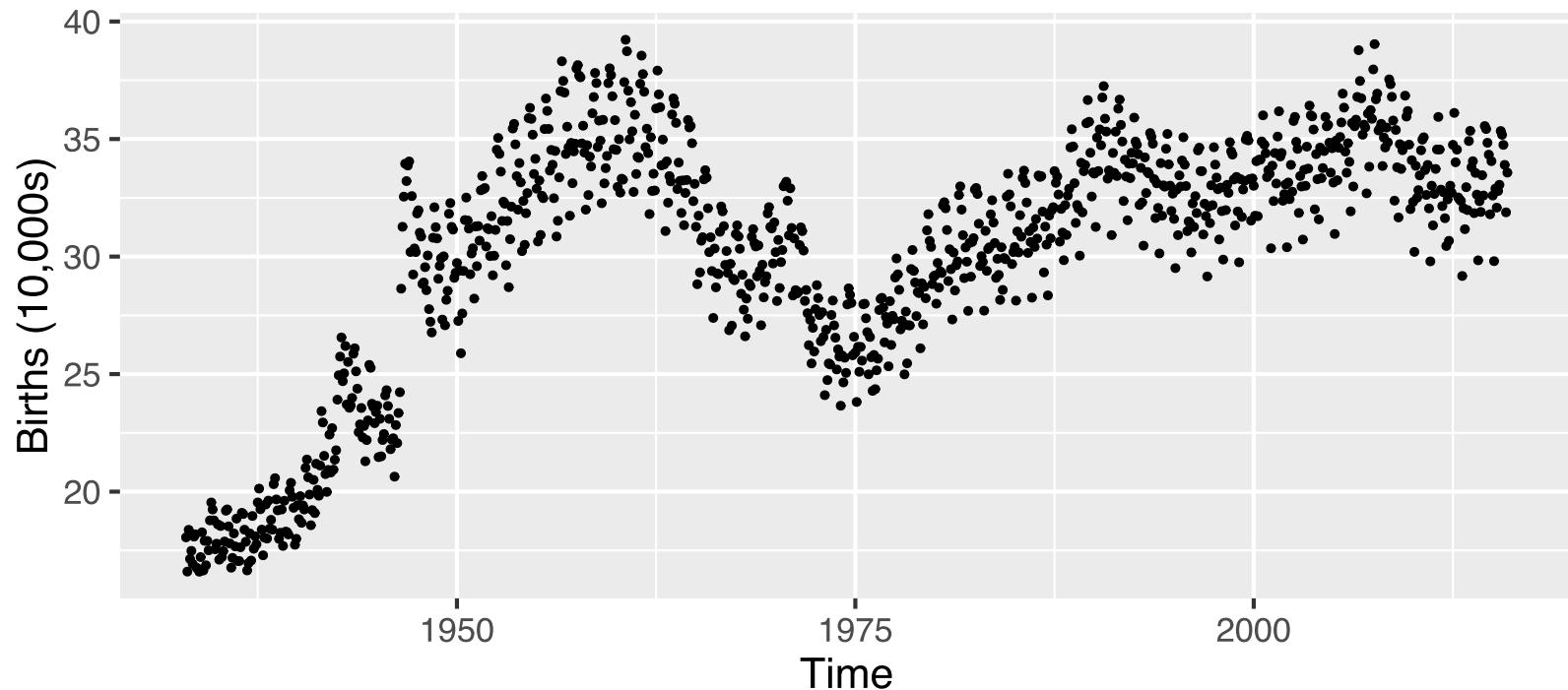
```
ggplot(data = birth_df, aes(x = time, y = births/10000)) +  
  geom_point(aes(color = post_ww2))
```



# ggplot2

## Add labels

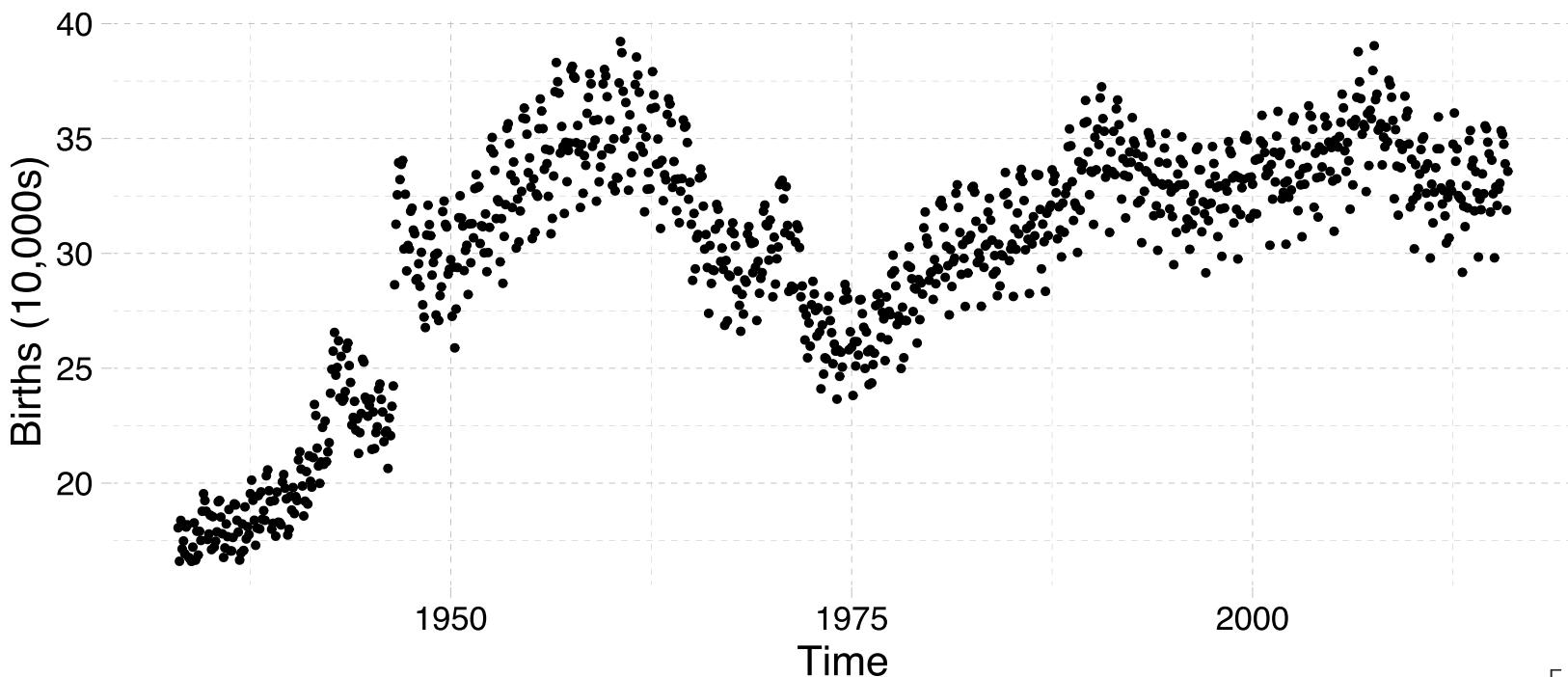
```
ggplot(data = birth_df, aes(x = time, y = births/10000)) +  
  geom_point() +  
  xlab("Time") + ylab("Births (10,000s)")
```



# ggplot2

Change the theme...

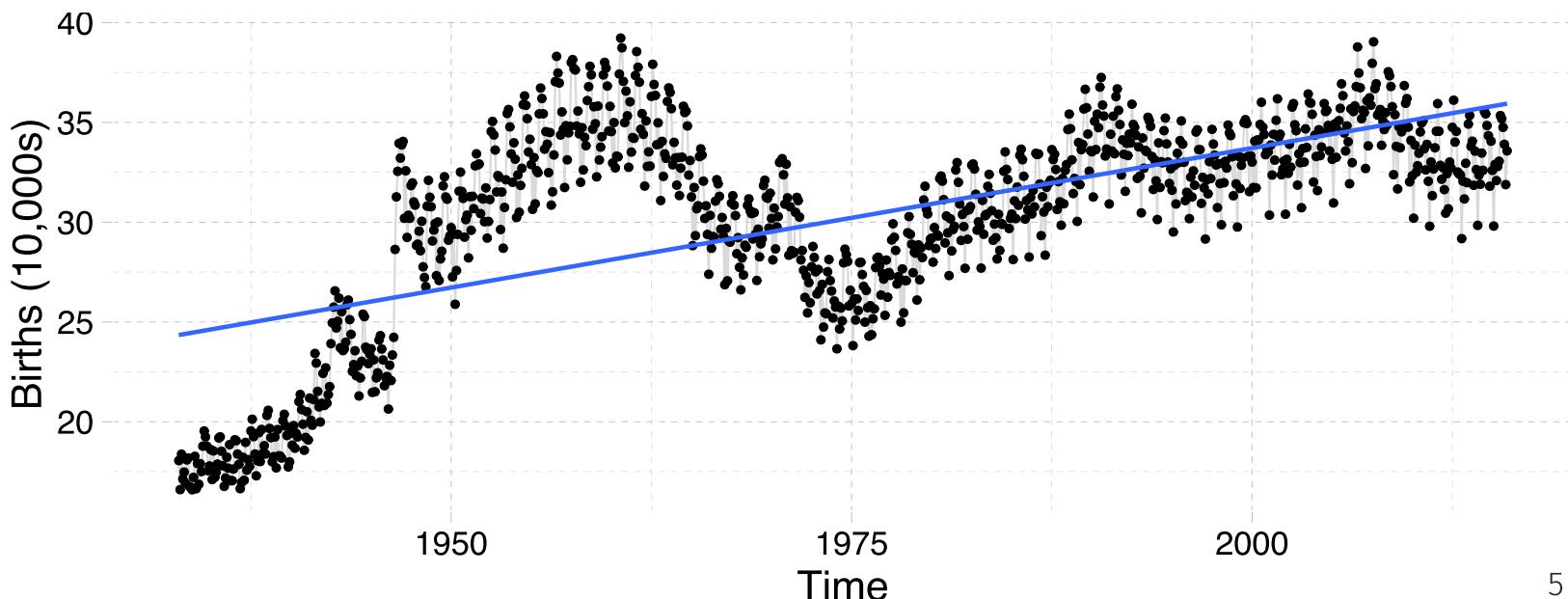
```
ggplot(data = birth_df, aes(x = time, y = births/10000)) +  
  geom_point() +  
  xlab("Time") + ylab("Births (10,000s)") +  
  theme_pander(base_size = 20)
```



# ggplot2

Add other geometries—e.g., connect the dots (`line`) and a regression line

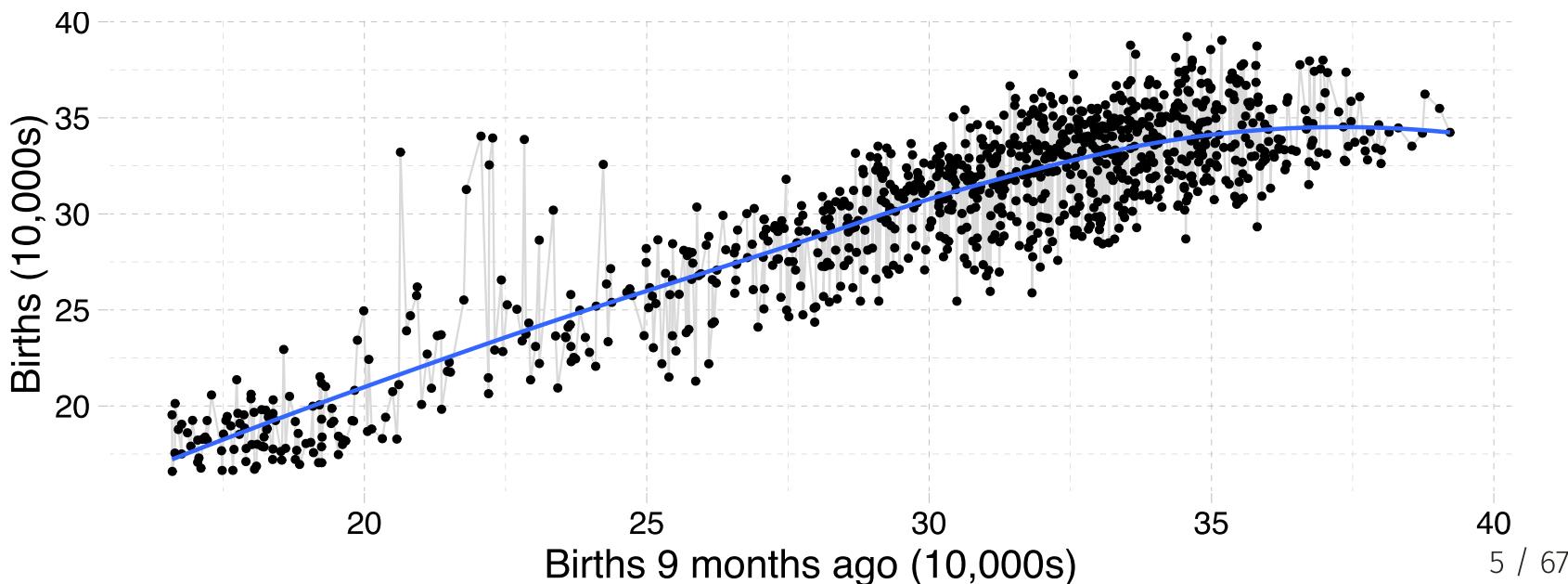
```
ggplot(data = birth_df, aes(x = time, y = births/10000)) +  
  geom_line(color = "grey85") +  
  geom_point() +  
  geom_smooth(se = F, method = lm) +  
  xlab("Time") + ylab("Births (10,000s)") +  
  theme_pander(base_size = 20)
```



# ggplot2

Compare births and its 9-month lag...

```
ggplot(data = birth_df, aes(x = lag(births, 9)/10000, y = births/10000)) +  
  geom_line(color = "grey85") +  
  geom_point() +  
  geom_smooth(se = F) +  
  xlab("Births 9 months ago (10,000s)") + ylab("Births (10,000s)") +  
  theme_pander(base_size = 20)
```



# Writing functions

## Functions are everywhere

Everything you do in R involves some sort of function, *e.g.*,

- `mean()`
- `lm()`
- `summary()`
- `read_csv()`
- `ggplot()`
- `+`

The basic idea in R is doing things to objects with functions.

# Writing functions

## Functions can help

We write functions to make life easier. Instead of copying and pasting the same line of code a million times, you can write one function.

In R, you use the `function()` function to write functions.<sup>†</sup>

```
# Our first function
the_name ← function(arg1, arg2) {
  # Insert code that involves arg1 and arg2 (this is where the magic happens)
}
```

- `the_name`: The name we are giving to our new function.
- `arg1`: The first argument of our function.
- `arg2`: The second argument of our function.

<sup>†</sup> Meta, right?

# Writing functions

## Our first real function

Let's write a function that multiplies two numbers. (It needs two arguments.)

```
# Create our function
the_product <- function(x, y) {
  x * y
}
```

# Writing functions

## Our first real function

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Did it work?

# Writing functions

## Our first real function

Let's write a function that multiplies two numbers. (It needs two arguments.)

```
# Create our function
the_product <- function(x, y) {
  x * y
}
```

Did it work?

```
the_product(7, 15)
```

```
#> [1] 105
```



# Writing functions

## Functions can do anything

... that you tell them.

If you are going to repeat a task (e.g., a simulation), then you have a good situation for writing your own function.

R offers many functions (via its many packages), but you will sometimes find a scenario for which no one has written a function.

Now you know how to write your own.

```
# An ad lib function
ad_lib <- function(noun1, noun2) {
  paste0("The next ", noun1, " of our lecture concerns the ", noun2, ".")
}
```

# Writing functions

```
ad_lib(noun1 = "part", noun2 = "midterm")
```

```
#> [1] "The next part of our lecture concerns the midterm."
```

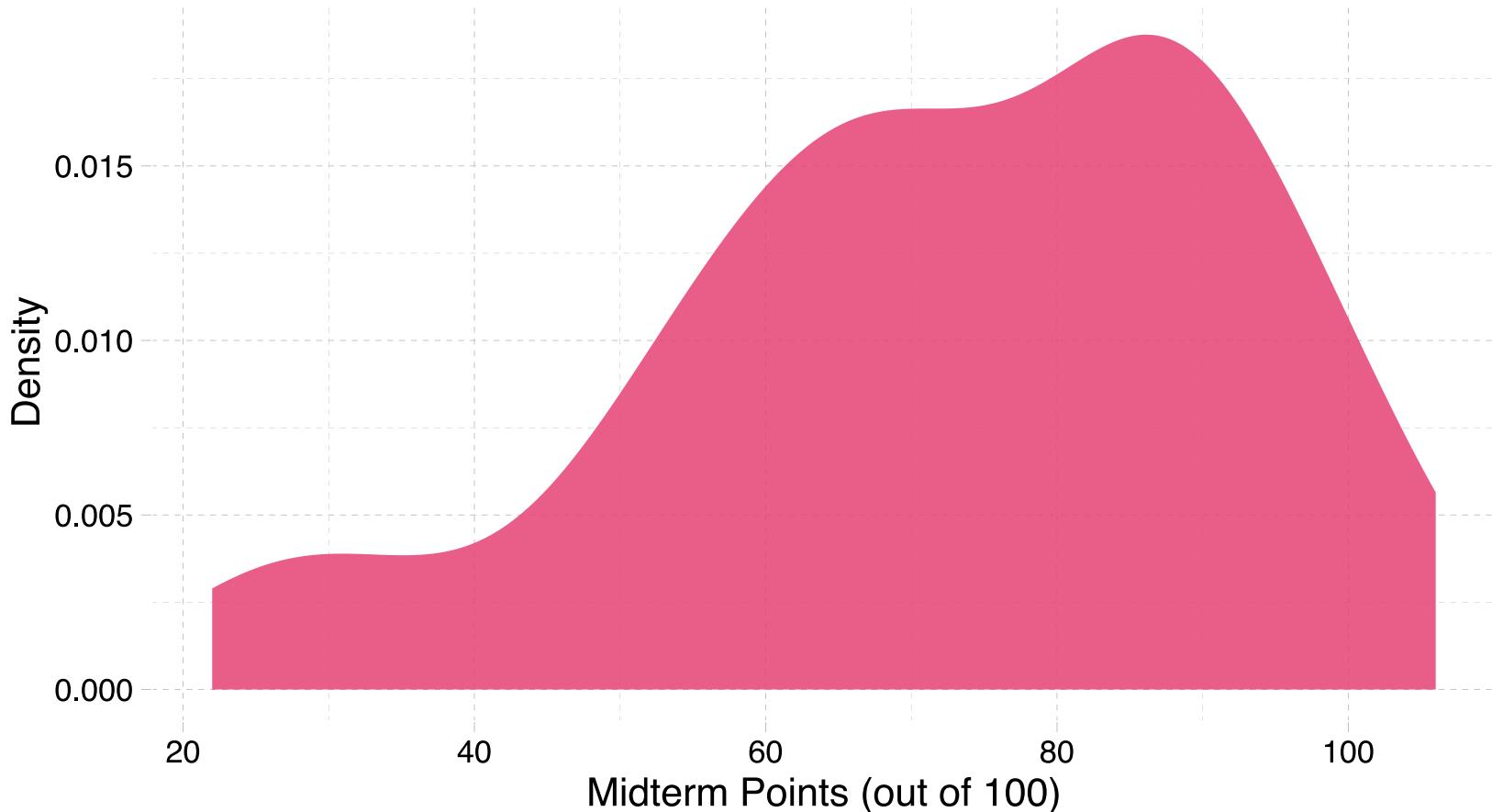
# Midterm

## Summary of the midterm grades

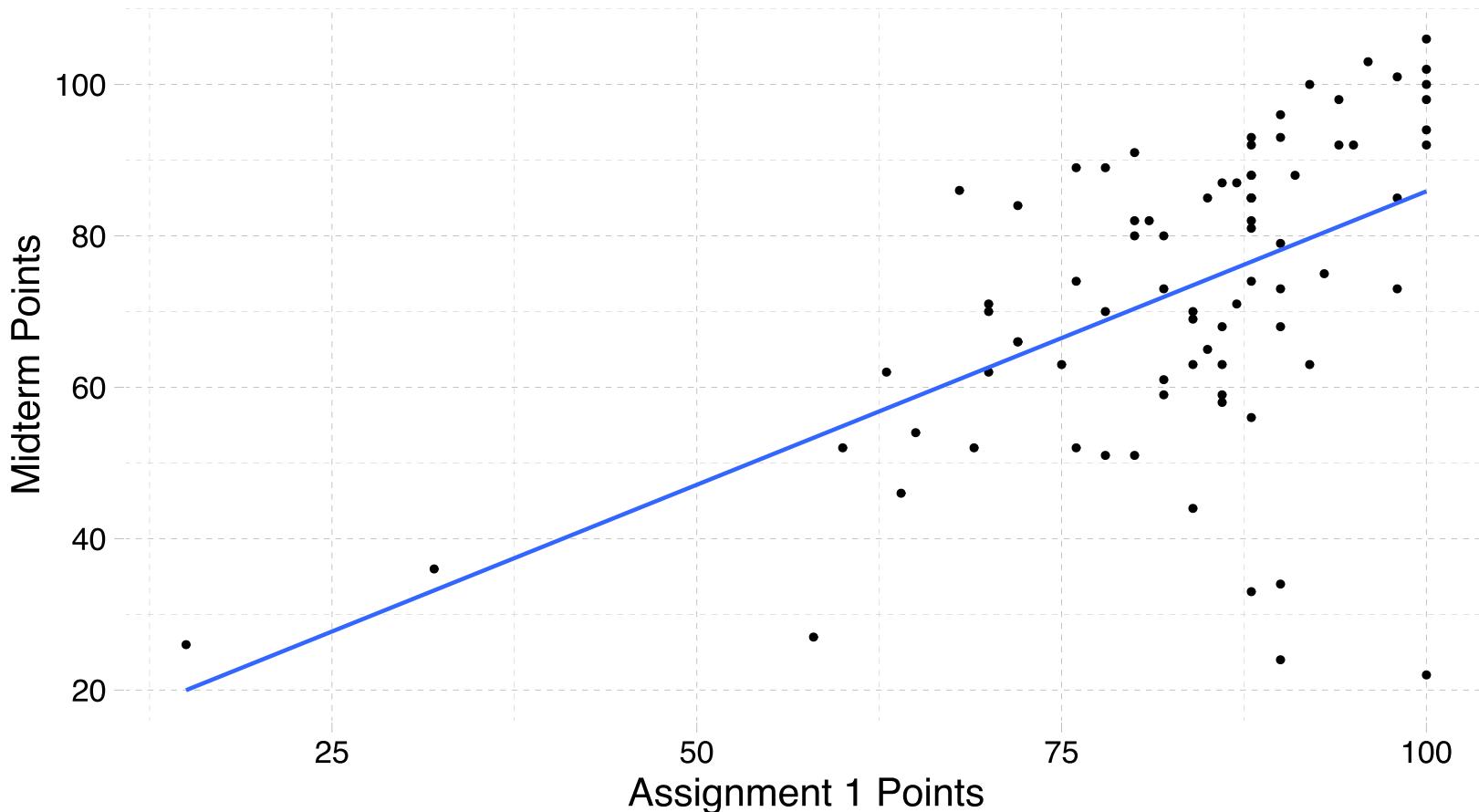
The **mean** midterm grade was 72.5.

- *Minimum:* 22
- *25<sup>th</sup> percentile:* 61.2
- *Median:* 73.5
- *75<sup>th</sup> percentile:* 88
- *Maximum:* 106

```
ggplot(data = grades_df, aes(x = midterm)) +  
  geom_density(color = NA, fill = red_pink, alpha = 0.85) +  
  labs(x = "Midterm Points (out of 100)", y = "Density") +  
  theme_pander(base_size = 20)
```



```
ggplot(data = grades_df, aes(x = ps1, y = midterm)) +  
  geom_point() + geom_smooth(method = lm, se = F) +  
  labs(x = "Assignment 1 Points", y = "Midterm Points") +  
  theme_pander(base_size = 20)
```



# Time series

*Review*

# Time series

## Review

Changes to our model/framework.

- Our model now has  $t$  subscripts for **time periods**.
- **Dynamic models** allow **lags** of explanatory and/or outcome variables.
- We changed our **exogeneity** assumption to **contemporaneous exogeneity**, i.e.,  $\mathbf{E}[u_t | X_t] = 0$
- Including **lags of outcome variables** can lead to **biased coefficient estimates** from OLS.
- **Lagged explanatory variables** make **OLS inefficient**.

# Autocorrelation

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## What is it?

**Autocorrelation** occurs when our disturbances are correlated over time, *i.e.*,  $\text{Cov}(u_t, u_s) \neq 0$  for  $t \neq s$ .

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Another way to think about: If the *shock* from disturbance  $t$  correlates with "nearby" shocks in  $t - 1$  and  $t + 1$ .

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Note: **Serial correlation** and **autocorrelation** are the same thing.

# Autocorrelation

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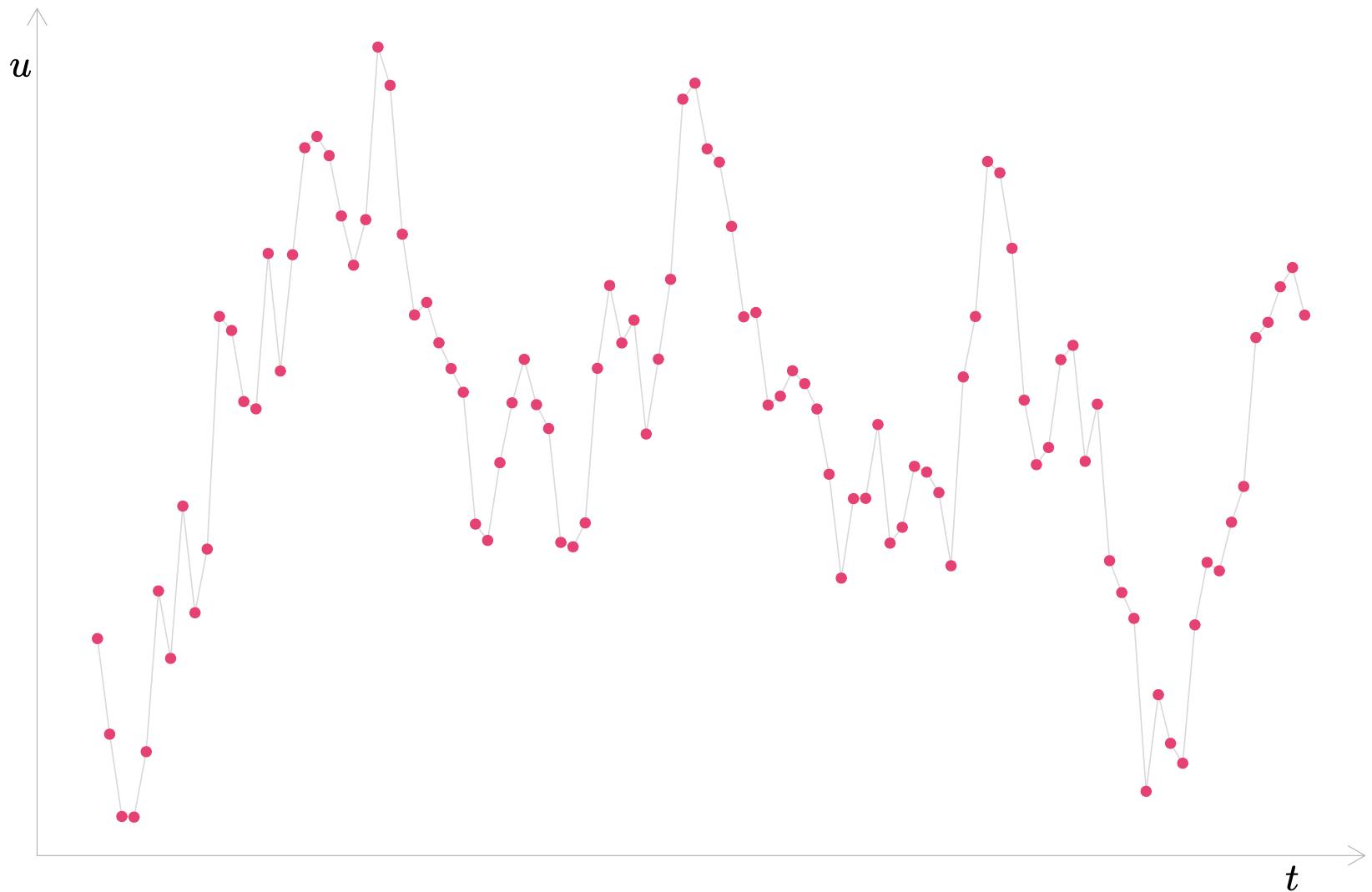
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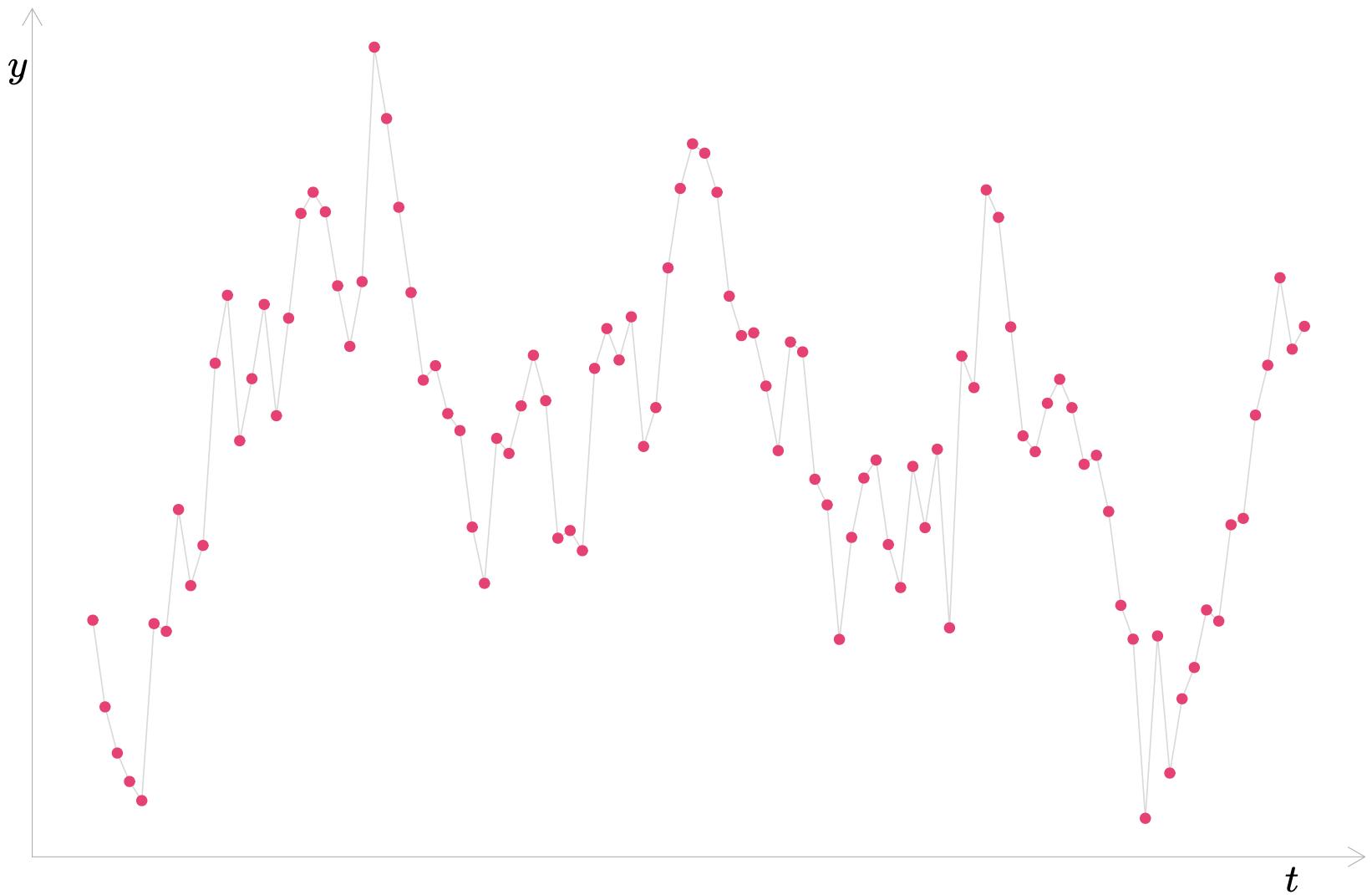
Note: **Serial correlation** and **autocorrelation** are the same thing.

Why is autocorrelation prevalent in time-series analyses?

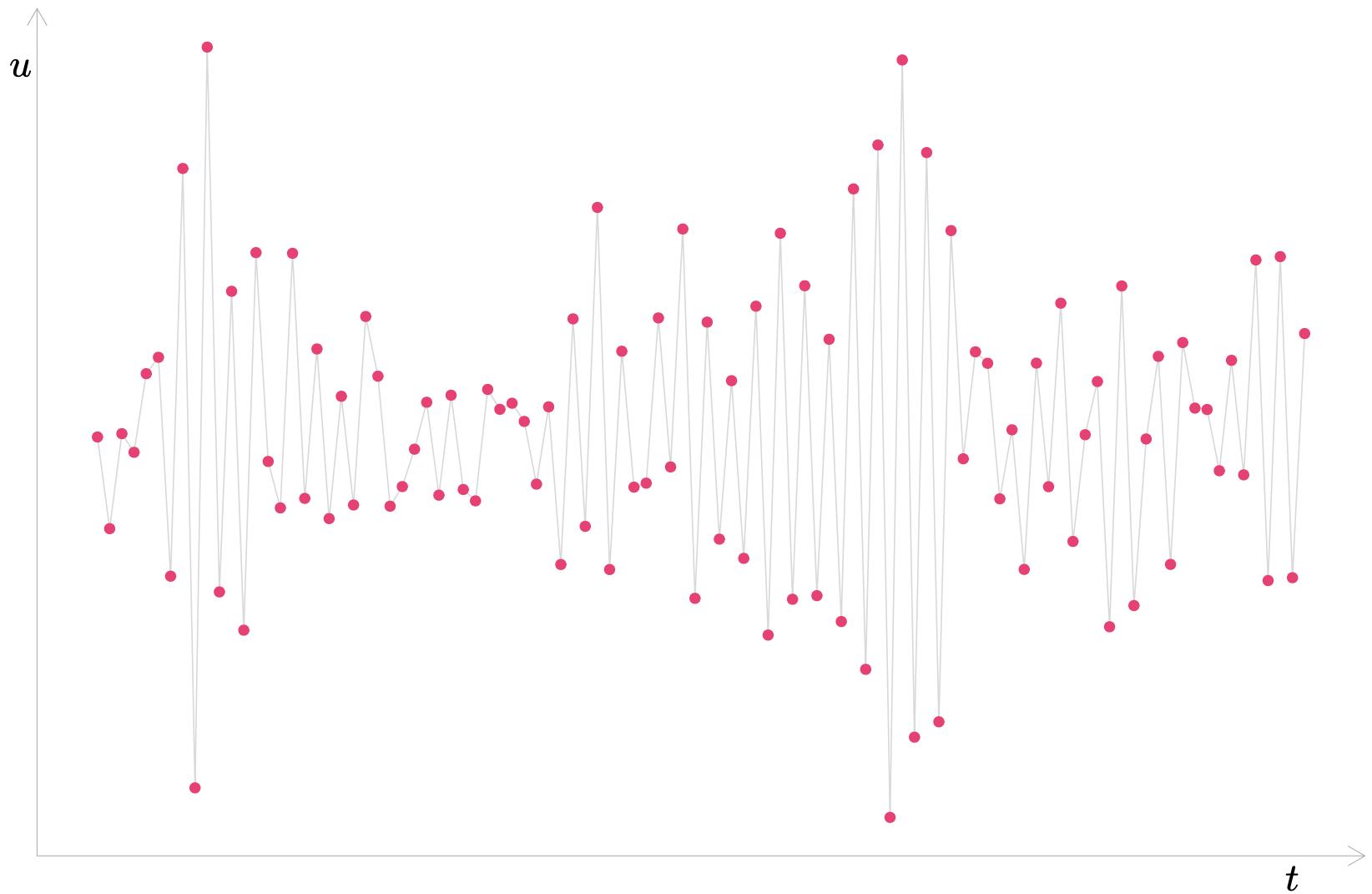
## Positive autocorrelation: Disturbances ( $u_t$ ) over time



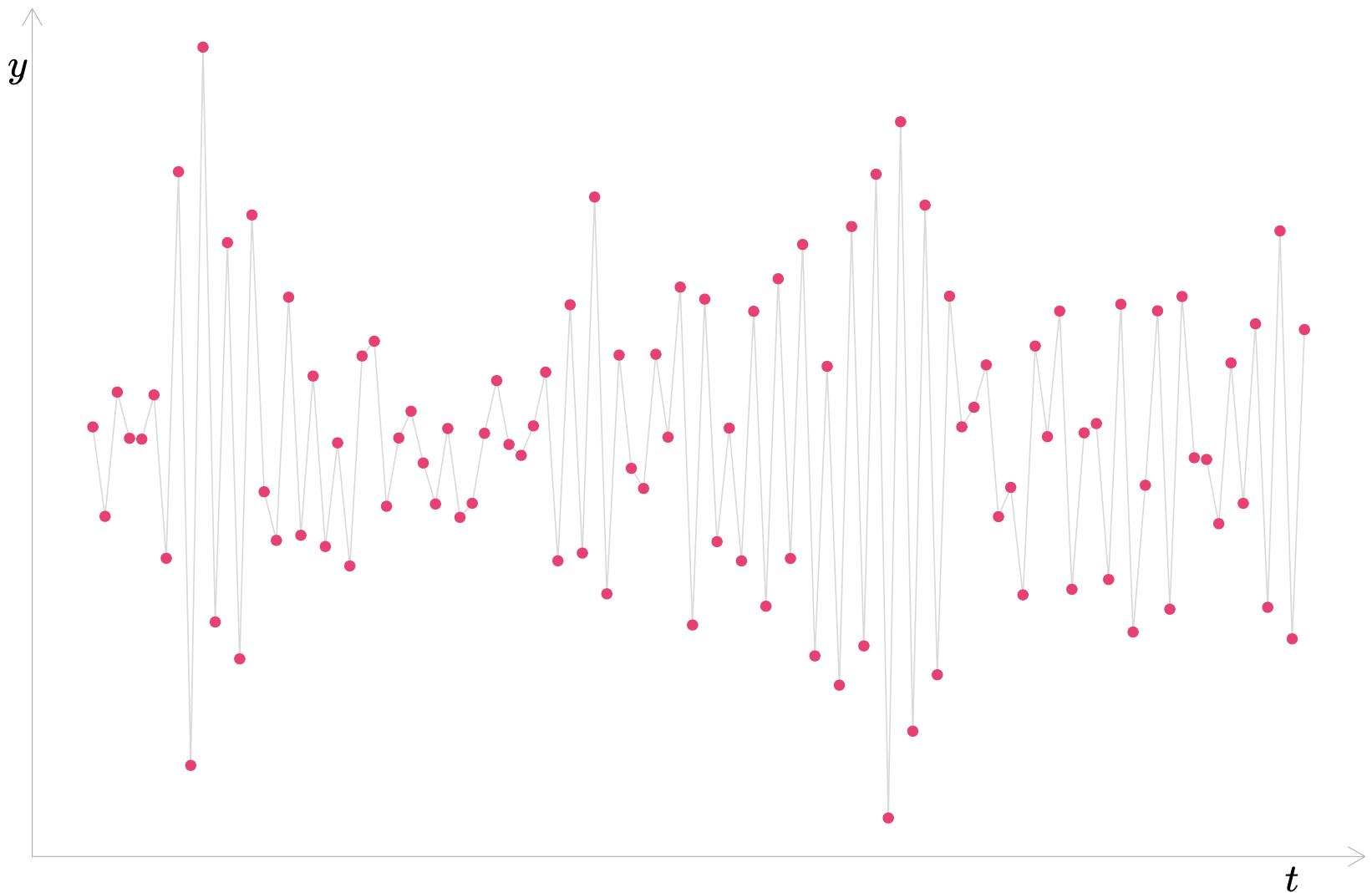
## Positive autocorrelation: Outcomes ( $y_t$ ) over time



## Negative autocorrelation: Disturbances ( $u_t$ ) over time



## Negative autocorrelation: Outcomes ( $y_t$ ) over time



# Autocorrelation

## In static time-series models

Let's start with a very common model: a static time-series model whose disturbances exhibit **first-order autocorrelation**, *a.k.a.* AR(1):

$$\text{Births}_t = \beta_0 + \beta_1 \text{Income}_t + u_t$$

where

$$u_t = \rho u_{t-1} + \varepsilon_t$$

and the  $\varepsilon_t$  are independently and identically distributed (*i.i.d.*).

# Autocorrelation

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**Second-order autocorrelation**, or AR(2), would be

$$u_t = \rho_1 u_{t-1} + \rho_2 u_{t-2} + \varepsilon_t$$

# Autocorrelation

## In static time-series models

An AR( $p$ ) model/process has a disturbance structure of

$$u_t = \sum_{j=1}^p \rho_j u_{t-j} + \varepsilon_t$$

allowing the current disturbance to correlated with up to  $p$  of its lags.

# Autocorrelation

## OLS

For **static models** or **dynamic models with lagged explanatory variables**, in the presence of autocorrelation

1. OLS provides **unbiased** estimates for the coefficients.
2. OLS creates **biased** estimates for the standard errors.
3. OLS is **inefficient**.

*Recall:* Same implications as heteroskedasticity.

Autocorrelation get trickier with lagged outcome variables.

# Autocorrelation

## OLS and lagged outcome variables

Consider a model with one lag of the outcome variable—ADL(1, 0)—model with AR(1) disturbances

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**Problem:**

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**Problem:** Both  $\text{Births}_{t-1}$  (a regressor in the model for time  $t$ ) and  $u_t$  (the disturbance for time  $t$ ) depend upon  $u_{t-1}$ . *i.e.*, a regressor is correlated with its contemporaneous disturbance.

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**A:** It violates **contemporaneous exogeneity**

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**Q:** Why is this a problem?

**A:** It violates **contemporaneous exogeneity**, *i.e.*,  $\text{Cov}(x_t, u_t) \neq 0$ .

# Autocorrelation

## OLS and lagged outcome variables

To see this problem, first write out the model for  $t$  and  $t - 1$ :

$$\text{Births}_t = \beta_0 + \beta_1 \text{Income}_t + \beta_2 \text{Births}_{t-1} + u_t$$

$$\text{Births}_{t-1} = \beta_0 + \beta_1 \text{Income}_{t-1} + \beta_2 \text{Births}_{t-2} + u_{t-1}$$

and now note that  $u_t = \rho u_{t-1} + \varepsilon_t$ . Substituting...

$$\text{Births}_t = \beta_0 + \beta_1 \text{Income}_t + \beta_2 \text{Births}_{t-1} + \overbrace{(\rho u_{t-1} + \varepsilon_t)}^{u_t} \quad (1)$$

$$\text{Births}_{t-1} = \beta_0 + \beta_1 \text{Income}_{t-1} + \beta_2 \text{Births}_{t-2} + u_{t-1} \quad (2)$$

In (1), we can see that  $u_t$  depends upon (covaries with)  $u_{t-1}$ .

In (2), we can see that  $\text{Births}_{t-1}$ , a regressor in (1), also covaries with  $u_{t-1}$ .

# Autocorrelation

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In (2), we can see that  $\text{Births}_{t-1}$ , a regressor in (1), also covaries with  $u_{t-1}$ .

∴ This model violates our contemporaneous exogeneity requirement.

# Autocorrelation

## OLS and lagged outcome variables

*Implications:* For models with **lagged outcome variables** and **autocorrelated disturbances**

1. The models **violate contemporaneous exogeneity**.
2. OLS is **biased and inconsistent** for the coefficients.

# Autocorrelation

## OLS and lagged outcome variables

*Intuition?* Why is OLS inconsistent and biased when we violate exogeneity?

Think back to omitted-variable bias...

$$y_t = \beta_0 + \beta_1 x_t + u_t$$

When  $\text{Cov}(x_t, u_t) \neq 0$ , we cannot separate the effect of  $u_t$  on  $y_t$  from the effect of  $x_t$  on  $y_t$ . Thus, we get inconsistent estimates for  $\beta_1$ .

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we cannot separate the effects of  $u_t$  on  $\text{Births}_t$  from  $\text{Births}_{t-1}$  on  $\text{Births}_t$ , because both  $u_t$  and  $\text{Births}_{t-1}$  depend upon  $u_{t-1}$ .

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# Autocorrelation and bias

## Simulation

To see how this bias can look, let's run a simulation.

$$y_t = 1 + 2x_t + 0.5y_{t-1} + u_t$$

$$u_t = 0.9u_{t-1} + \varepsilon_t$$

One (easy) way generate 100 disturbances from AR(1), with  $\rho = 0.9$ :

```
arima.sim(model = list(ar = c(0.9)), n = 100)
```

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**Q:** Will this simulation tell us about *bias* or *consistency*?

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We are going to run 10,000 iterations with  $T = 100$ .

**Q:** Will this simulation tell us about *bias* or *consistency*?

**A:** Bias. We would need to let  $T \rightarrow \infty$  to consider consistency.

# Autocorrelation and bias

## Simulation

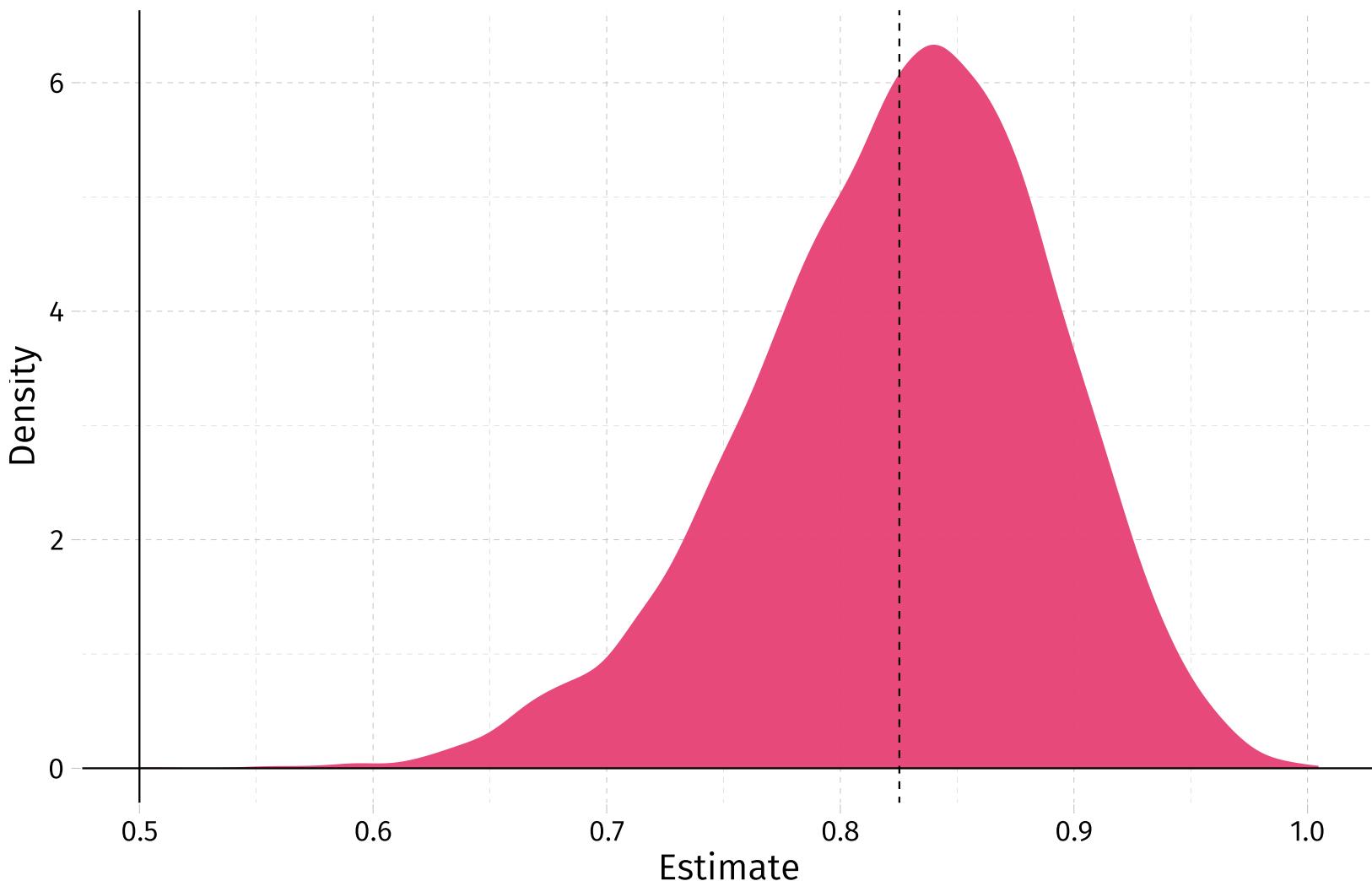
Outline of our simulation:

1. Generate  $T=100$  values of  $x$
2. Generate  $T=100$  values of  $u$ 
  - Generate  $T=100$  values of  $\varepsilon$
  - Use  $\varepsilon$  and  $\rho=0.9$  to calculate  $u_t = \rho u_{t-1} + \varepsilon_t$
3. Calculate  $y_t = \beta_0 + \beta_1 x_t + \beta_2 y_{t-1} + u_t$
4. Regress  $y$  on  $x$ ; record estimates

Repeat 1-4 10,000 times

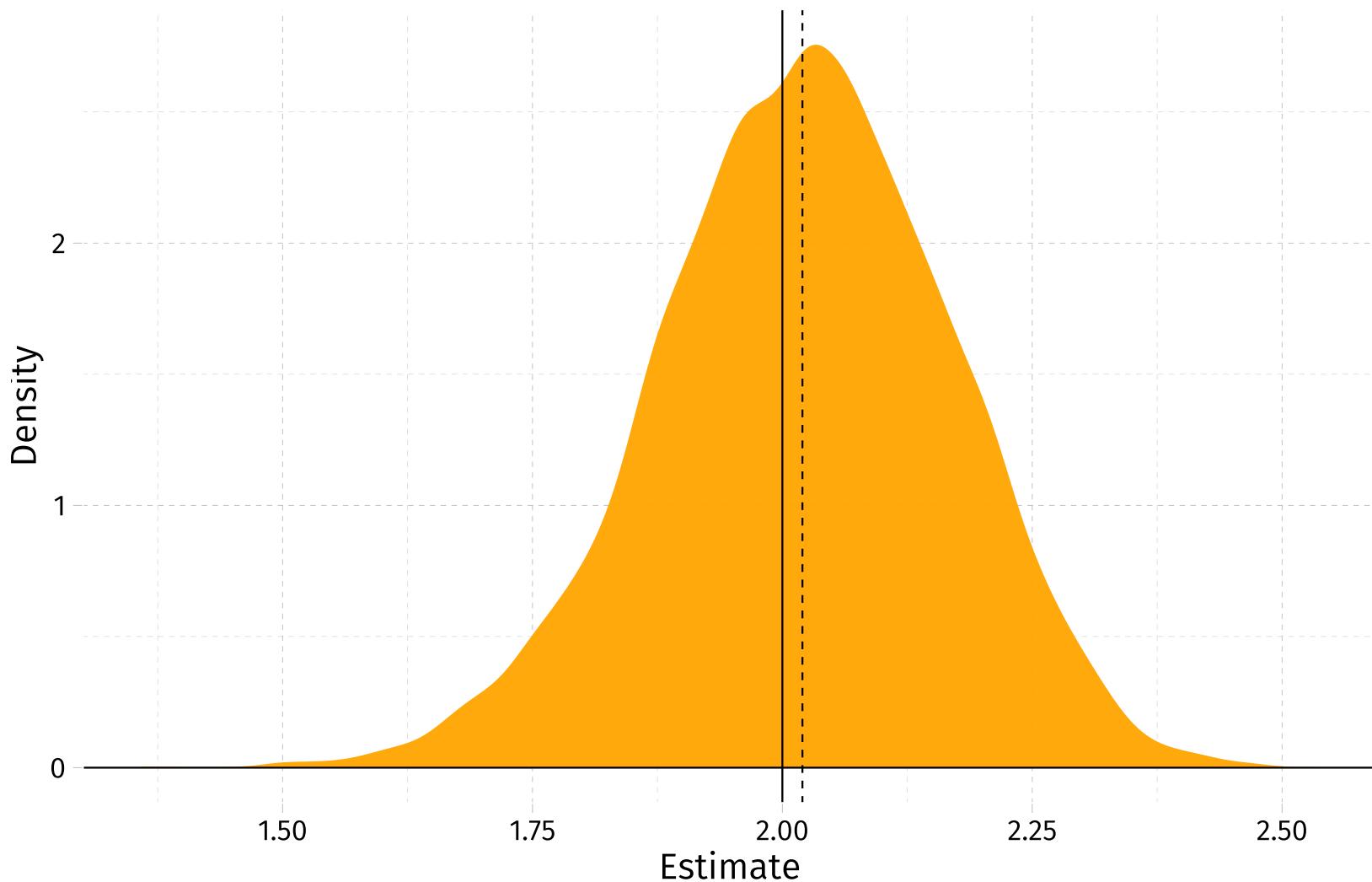
## Distribution of OLS estimates, $\hat{\beta}_2$

$$y_t = 1 + 2x_t + 0.5y_{t-1} + u_t$$



## Distribution of OLS estimates, $\hat{\beta}_1$

$$y_t = 1 + 2x_t + 0.5y_{t-1} + u_t$$



# Testing for autocorrelation

# Testing for autocorrelation

## Static models

Suppose we have the **static model**,

$$\text{Births}_t = \beta_0 + \beta_1 \text{Income}_t + u_t \quad (\text{A})$$

and we want to test for an AR(1) process in our disturbances  $u_t$ .

# Testing for autocorrelation

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**Test for autocorrelation:** Test for correlation in the lags of our residuals:

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$$e_t = \rho e_{t-1} + v_t$$

# Testing for autocorrelation

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Does  $\hat{\rho}$  differ significantly from zero?

# Testing for autocorrelation

## Static models

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**Test for autocorrelation:** Test for correlation in the lags of our residuals:

$$e_t = \rho e_{t-1} + v_t$$

Does  $\hat{\rho}$  differ significantly from zero?

**Familiar idea:** Use residuals to learn about disturbances.

# Testing for autocorrelation

## Static models

Specifically, to test for AR(1) disturbances in the static model

$$\text{Births}_t = \beta_0 + \beta_1 \text{Income}_t + u_t \quad (\text{A})$$

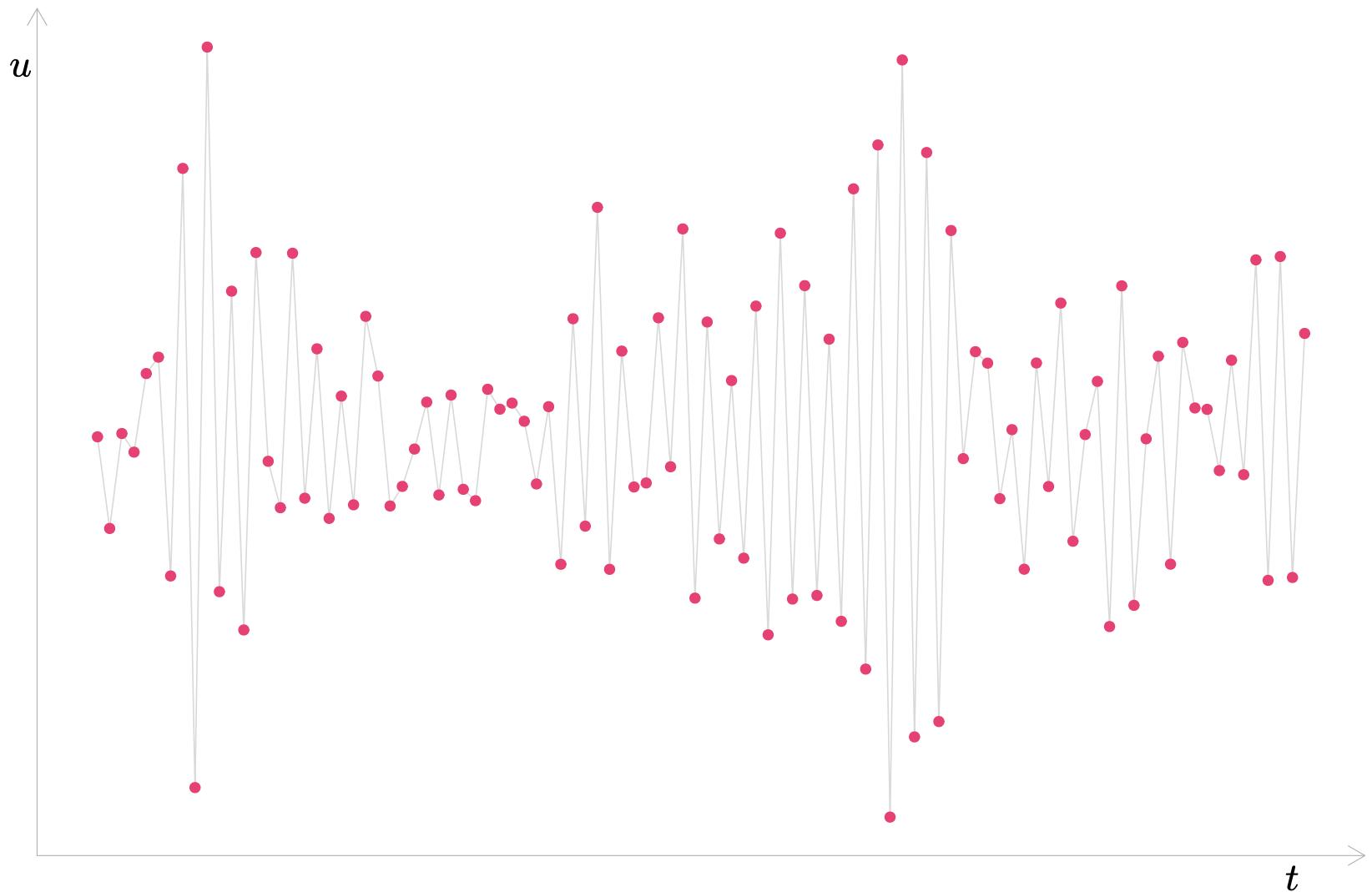
1. Estimate (A) via OLS.
2. Calculate residuals from the OLS regression in step 1.
3. Regress the residuals on their lags (without an intercept).

$$e_t = \rho e_{t-1} + v_t$$

4. Use a  $t$  test to determine whether there is statistically significant evidence that  $\rho$  differs from zero.
5. Rejecting  $H_0$  implies significant evidence of autocorrelation.

For an example, let's return to our plot of negative autocorrelation.

## Negative autocorrelation: Disturbances ( $u_t$ ) over time



# Testing for autocorrelation

## Example: Static model and AR(1)

**Step 1:** Estimate the static model ( $y_t = \beta_0 + \beta_1 x_t + u_t$ ) with OLS

```
reg_est ← lm(y ~ x, data = ar_df)
```

# Testing for autocorrelation

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```
ar_df$e ← residuals(reg_est)
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```
reg_est ← lm(y ~ x, data = ar_df)
```

**Step 2:** Add the residuals to our dataset

```
ar_df$e ← residuals(reg_est)
```

**Step 3:** Regress the residual on its lag (**no intercept**)

```
reg_resid ← lm(e ~ -1 + lag(e), data = ar_df)
```

# Testing for autocorrelation

## Example: Static model and AR(1)

**Step 4:**  $t$  test for the estimated ( $\hat{\rho}$ ) coefficient in step 3.

```
tidy(reg_resid)
```

```
#> # A tibble: 1 × 5
#>   term    estimate std.error statistic p.value
#>   <chr>     <dbl>     <dbl>     <dbl>     <dbl>
#> 1 lag(e)   -0.851     0.0535    -15.9  6.88e-29
```

# Testing for autocorrelation

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That's a very small  $p$ -value—much smaller than 0.05.

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**Reject  $H_0$**  ( $H_0$  was  $\rho = 0$ , i.e., no autocorrelation).

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That's a very small  $p$ -value—much smaller than 0.05.

**Reject  $H_0$**  ( $H_0$  was  $\rho = 0$ , i.e., no autocorrelation).

**Step 5:** Conclude. Statistically significant evidence of autocorrelation.

# Testing for autocorrelation

## Example: Static model and AR(3)

What if we wanted to test for AR(3)?

- We add more lags of residuals to the regression in *Step 3*.
- We **jointly** test the significance of the coefficients (*i.e.*, LM or  $F$ ).

Let's do it.

# Testing for autocorrelation

## Example: Static model and AR(3)

**Step 1:** Estimate the static model ( $y_t = \beta_0 + \beta_1 x_t + u_t$ ) with OLS

```
reg_est ← lm(y ~ x, data = ar_df)
```

# Testing for autocorrelation

## Example: Static model and AR(3)

**Step 1:** Estimate the static model ( $y_t = \beta_0 + \beta_1 x_t + u_t$ ) with OLS

```
reg_est ← lm(y ~ x, data = ar_df)
```

**Step 2:** Add the residuals to our dataset

```
ar_df$e ← residuals(reg_est)
```

# Testing for autocorrelation

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reg_est ← lm(y ~ x, data = ar_df)
```

**Step 2:** Add the residuals to our dataset

```
ar_df$e ← residuals(reg_est)
```

**Step 3:** Regress the residual on its lag (**no intercept**)

```
reg_ar3 ← lm(e ~ -1 + lag(e) + lag(e, 2) + lag(e, 3), data = ar_df)
```

# Testing for autocorrelation

## Example: Static model and AR(3)

**Step 1:** Estimate the static model ( $y_t = \beta_0 + \beta_1 x_t + u_t$ ) with OLS

```
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```
reg_ar3 ← lm(e ~ -1 + lag(e) + lag(e, 2) + lag(e, 3), data = ar_df)
```

Note: `lag(v, n)` from `dplyr` takes the  $n^{\text{th}}$  lag of the variable `v`.

# Testing for autocorrelation

## Example: Static model and AR(3)

**Step 4:** Calculate the  $\text{LM} = n \times R_e^2$  test statistic—distributed  $\chi_k^2$ .  
 $k$  is the number of regressors in the regression in Step 3 (here,  $k = 3$ ).

```
# Grab R squared
r2_e <- summary(reg_ar3)$r.squared
# Calculate the LM test statistic: n times r2_e
(lm_stat <- 100 * r2_e)
```

```
#> [1] 72.38204
```

```
# Calculate the p-value
(pchisq(q = lm_stat, df = 3, lower.tail = F))
```

```
#> [1] 1.318485e-15
```

# Testing for autocorrelation

Example: Static model and AR(3)

**Step 5:** Conclude.

# Testing for autocorrelation

Example: Static model and AR(3)

**Step 5:** Conclude.

*Recall:* Our hypotheses consider the model

$$e_t = \rho_1 e_{t-1} + \rho_2 e_{t-2} + \rho_3 e_{t-3}$$

# Testing for autocorrelation

## Example: Static model and AR(3)

**Step 5:** Conclude.

*Recall:* Our hypotheses consider the model

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which we are actually using to learn about the model

$$u_t = \rho_1 u_{t-1} + \rho_2 u_{t-2} + \rho_3 u_{t-3}$$

# Testing for autocorrelation

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$H_0: \rho_1 = \rho_2 = \rho_3 = 0$  vs.  $H_A: \rho_j \neq 0$  for at least one  $j$  in  $\{1, 2, 3\}$

Our p-value is less than 0.05.

# Testing for autocorrelation

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Our p-value is less than 0.05. **Reject  $H_0$ .**

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$$H_0: \rho_1 = \rho_2 = \rho_3 = 0 \quad \text{vs.} \quad H_A: \rho_j \neq 0 \text{ for at least one } j \text{ in } \{1, 2, 3\}$$

Our p-value is less than 0.05. **Reject  $H_0$ .**

Conclude there is statistically significant evidence of autocorrelation.

# Testing for autocorrelation

## Dynamic models with lagged outcome variables

**Recall:** OLS is biased and inconsistent when our model has *both*

1. a lagged dependent variable
2. autocorrelated disturbances

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∴ We can't apply our nice trick of just using  $e_t$  to learn about  $u_t$ .

**Solution:** **Breusch-Godfrey** test includes the other explanatory variables,

$$e_t = \underbrace{\gamma_0 + \gamma_1 x_{1t} + \gamma_2 x_{2t} + \cdots}_{\text{Explanatory variables}} + \underbrace{\rho_1 e_{t-1} + \rho_2 e_{t-2} + \cdots}_{\text{Lagged residuals}} + \varepsilon_t$$

# Testing for autocorrelation

## Dynamic models with lagged outcome variables

Specifically, to test for AR(2) disturbances in the ADL(1, 0) model

$$\text{Births}_t = \beta_0 + \beta_1 \text{Income}_t + \beta_2 \text{Births}_{t-1} + u_t \quad (\text{B})$$

1. Estimate (B) via OLS.
2. Calculate residuals ( $e_t$ ) from the OLS regression in step 1.
3. Regress residuals on an intercept, explanatory variables, and lagged residuals.

$$e_t = \gamma_0 + \gamma_1 \text{Income}_t + \rho_1 e_{t-1} + \rho_2 e_{t-2} + v_t$$

4. Conduct LM or F test for  $\rho_1 = \rho_2 = 0$ .
5. Rejecting  $H_0$  implies significant evidence of AR(2).

# Testing for autocorrelation

## Dynamic models with lagged outcome variables

For an example, let's consider the relationship between monthly presidential approval ratings and oil prices during President George W. Bush's<sup>†</sup> presidency.

We will specify the process as ADL(1, 0) and test for an AR(2) process in our disturbances.

$$\text{Approval}_t = \beta_0 + \beta_1 \text{Approval}_{t-1} + \beta_2 \text{Price}_t + u_t$$

<sup>†</sup> Fun with approval ratings.

# Testing for autocorrelation

## Dynamic models with lagged outcome variables

For an example, let's consider the relationship between monthly presidential approval ratings and oil prices during President George W. Bush's<sup>†</sup> presidency.

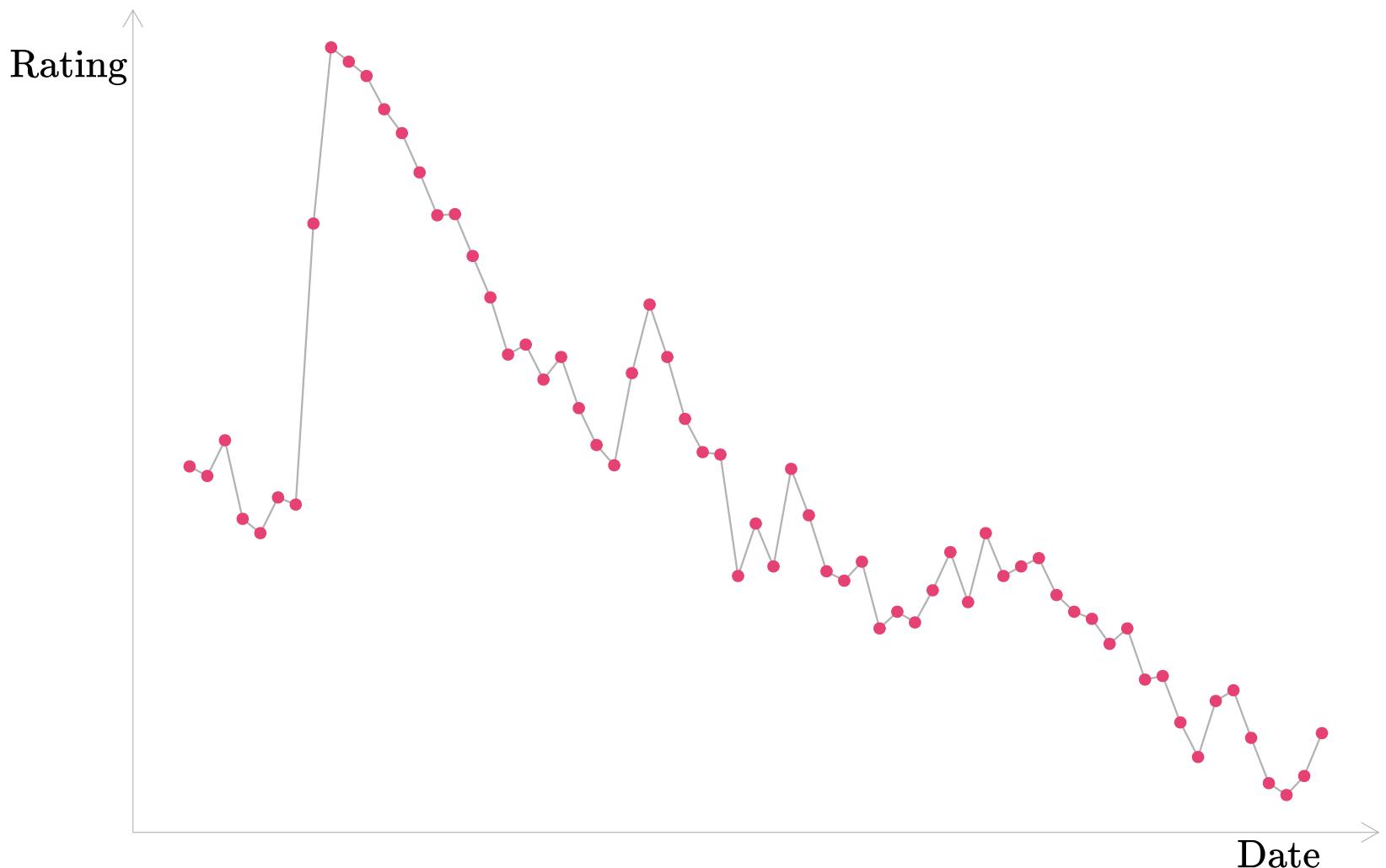
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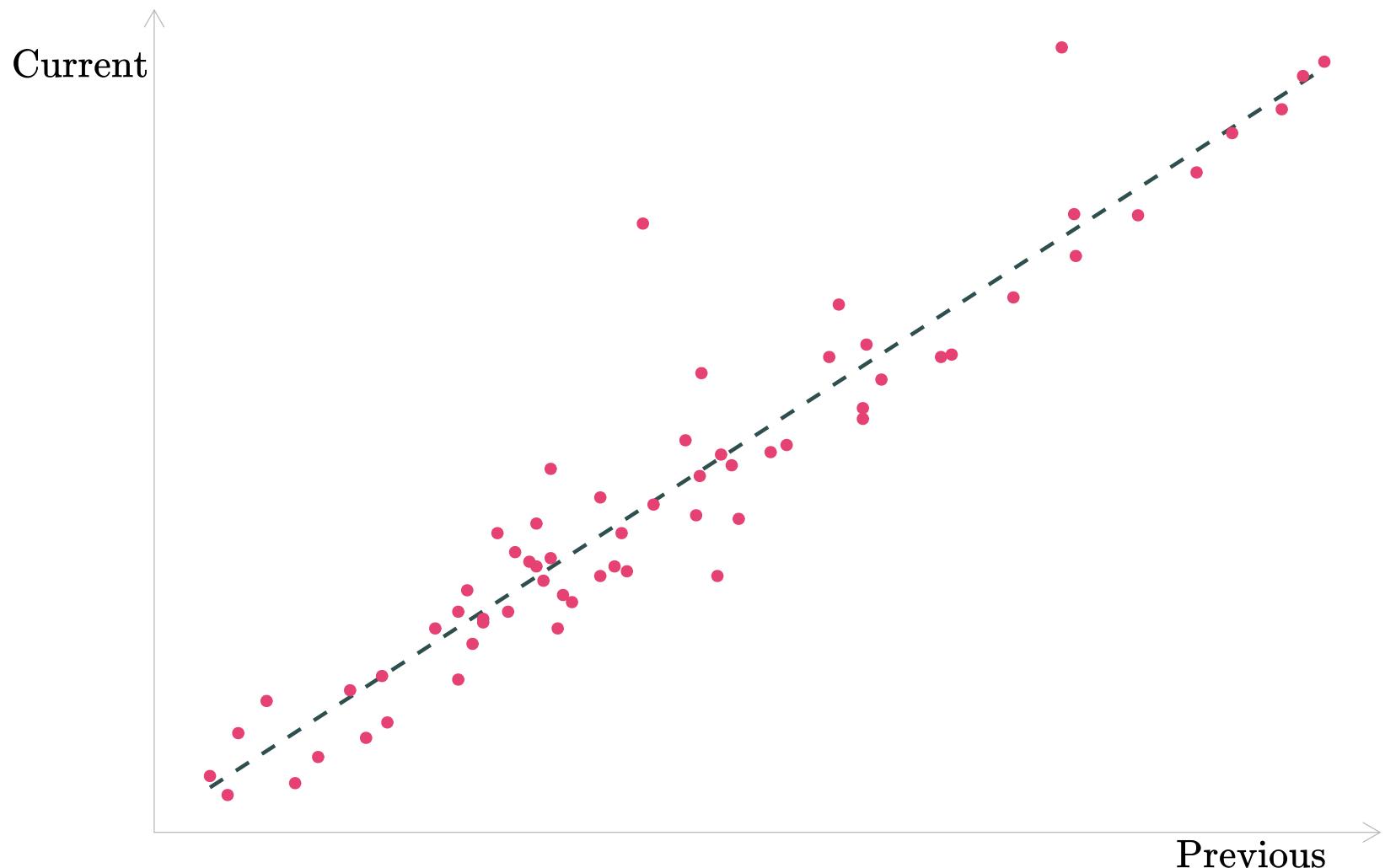
Note: We're ignoring any other violations of exogeneity for the moment.

<sup>†</sup> Fun with approval ratings.

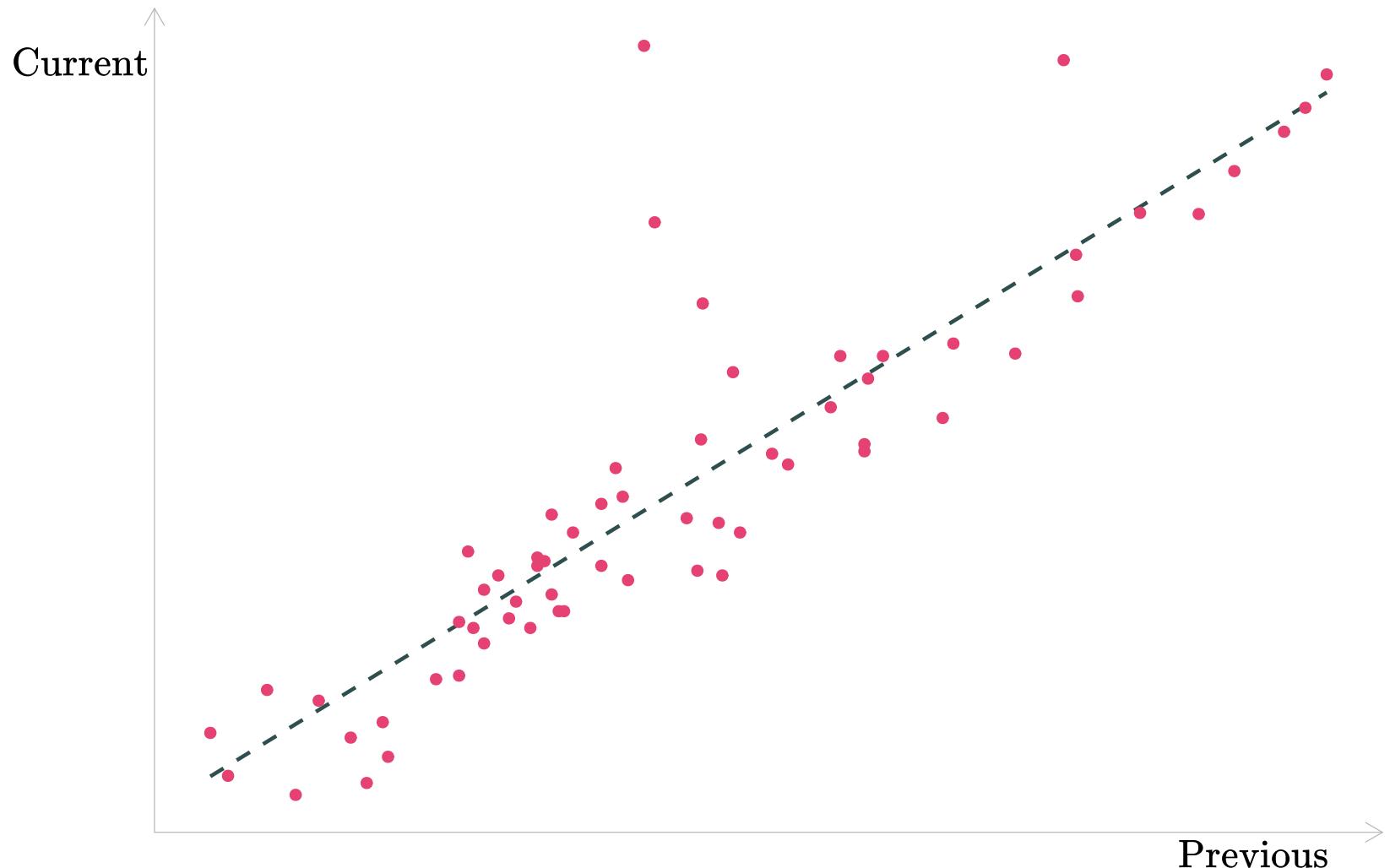
# Monthly presidential approval ratings, 2001–2006



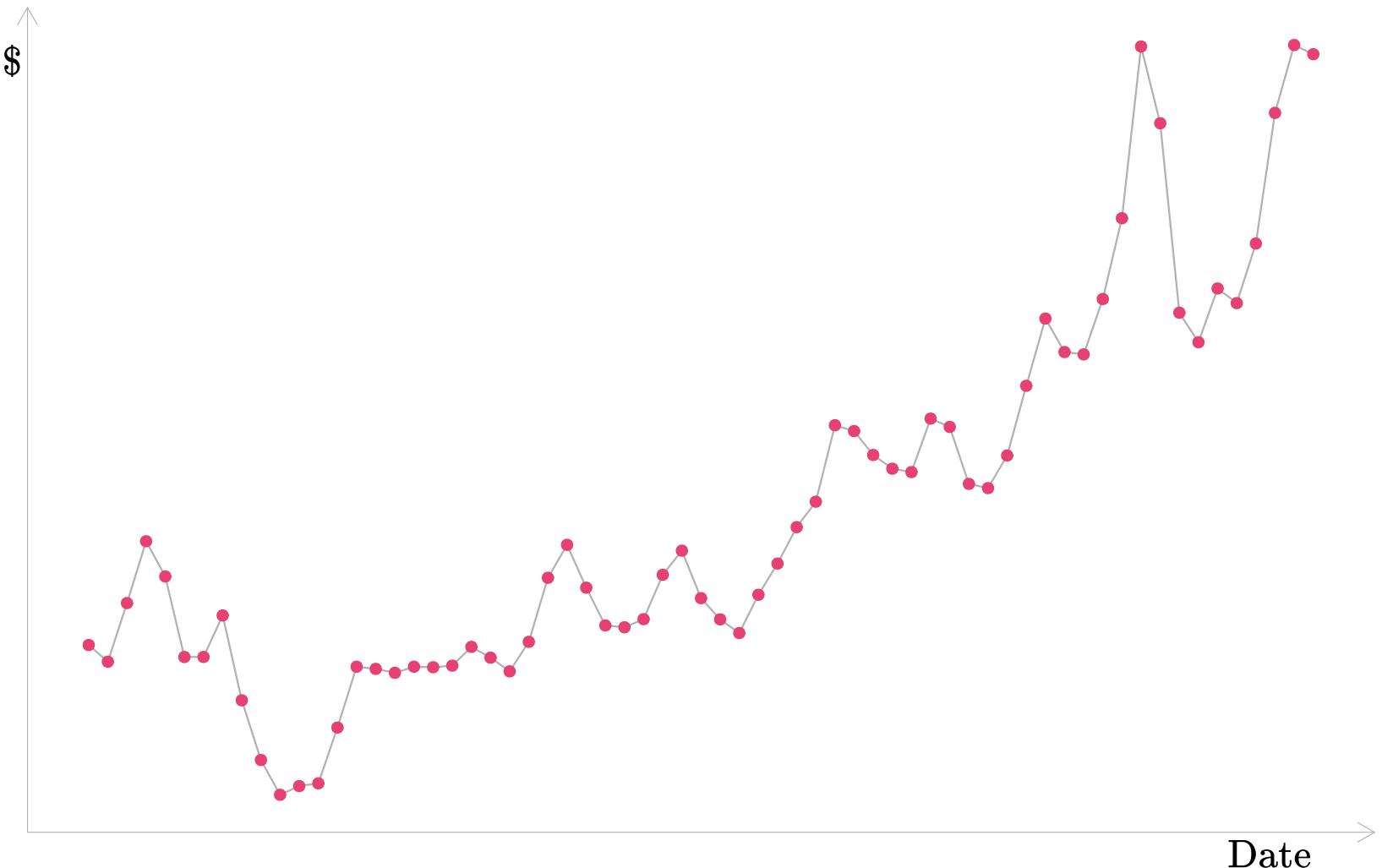
## Approval rating vs. its one-month lag, 2001–2006



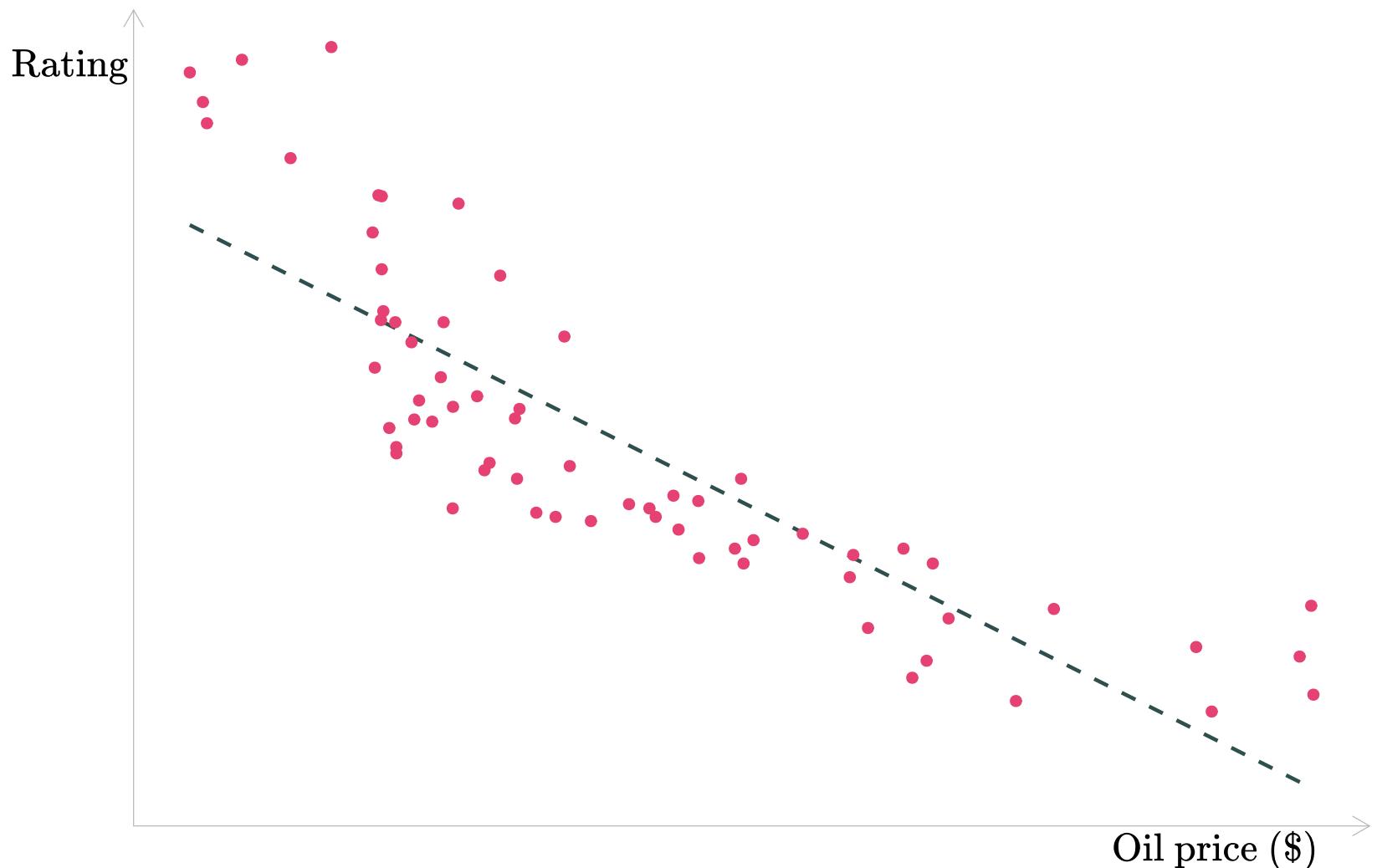
## Approval rating vs. its two-month lag, 2001–2006



## Oil prices, 2001–2006



## Approval rating vs. oil prices, 2001–2006



# Testing for autocorrelation

## Example: Approval ratings and oil prices

**Step 1:** Estimate our ADL(1, 0) model with OLS.

```
# Estimate the model
ols_est ← lm(
  ap ~ lag(approve) + price_oil,
  data = approval_df
)
# Summary
tidy(ols_est)
```

```
#> # A tibble: 3 × 5
#>   term      estimate std.error statistic p.value
#>   <chr>      <dbl>     <dbl>      <dbl>    <dbl>
#> 1 (Intercept)  16.2      7.86      2.06  4.40e- 2
#> 2 lag(approve)  0.841     0.0752     11.2   2.17e-16
#> 3 price_oil    -0.0410    0.0215     -1.90  6.15e- 2
```

# Testing for autocorrelation

## Example: Approval ratings and oil prices

**Step 2:** Record residuals from the OLS regression.

```
# Grab residuals
approval_df$e <- c(NA, residuals(ols_est))
```

# Testing for autocorrelation

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**Note:** We need to add an `NA` because we use a lag—the first element is missing.

# Testing for autocorrelation

## Example: Approval ratings and oil prices

**Step 2:** Record residuals from the OLS regression.

```
# Grab residuals  
approval_df$e <- c(NA, residuals(ols_est))
```

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*E.g.,*

```
{1, 2, 3, 4, 5, 6, 7, 8, 9} = x
```

# Testing for autocorrelation

## Example: Approval ratings and oil prices

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{1, 2, 3, 4, 5, 6, 7, 8, 9} = x
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```
{?, 1, 2, 3, 4, 5, 6, 7, 8} = lag(x)
```

# Testing for autocorrelation

## Example: Approval ratings and oil prices

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# Grab residuals  
approval_df$e <- c(NA, residuals(ols_est))
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```

```
{?, 1, 2, 3, 4, 5, 6, 7, 8} = lag(x)
```

```
{?, ?, 1, 2, 3, 4, 5, 6, 7} = lag(x, 2)
```

# Testing for autocorrelation

## Example: Approval ratings and oil prices

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# Grab residuals  
approval_df$e <- c(NA, residuals(ols_est))
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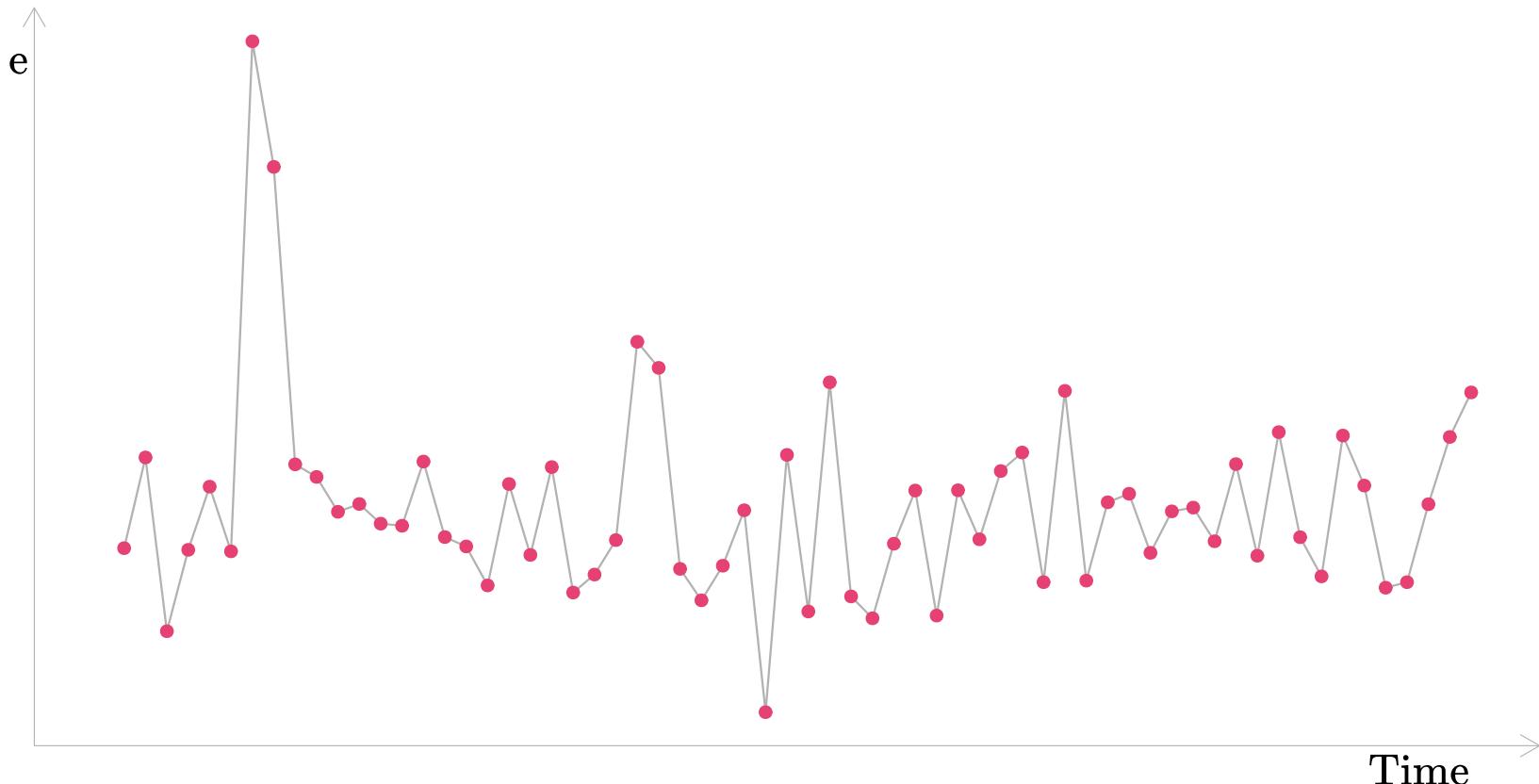
**Note:** We need to add an NA because we use a lag—the first element is missing.

E.g.,

```
{1, 2, 3, 4, 5, 6, 7, 8, 9} = x  
{?, 1, 2, 3, 4, 5, 6, 7, 8} = lag(x)  
{?, ?, 1, 2, 3, 4, 5, 6, 7} = lag(x, 2)  
{?, ?, ?, 1, 2, 3, 4, 5, 6} = lag(x, 3)
```

# Testing for autocorrelation

Example: Approval ratings and oil prices



# Testing for autocorrelation

## Example: Approval ratings and oil prices

**Step 3:** Regress residuals on an intercept, the explanatory variables, and lagged residuals.

```
# BG regression
bg_reg ← lm(
  e ~ lag(approve) + price_oil + lag(e) + lag(e, 2),
  data = approval_df
)
```

```
#>           Estimate Std. Error t value Pr(>|t|) 
#> (Intercept) 7.92474   9.30455   0.852   0.3979
#> lag(approve) -0.08503   0.09192  -0.925   0.3589
#> price_oil    -0.01690   0.02407  -0.702   0.4854
#> lag(e)        0.25236   0.14648   1.723   0.0903 .
#> lag(e, 2)     0.07865   0.14471   0.544   0.5889
```

# Testing for autocorrelation

## Example: Approval ratings and oil prices

**Step 4:**  $F$  (or LM) test for  $\rho_1 = \rho_2 = 0$ .

Recall: We can test joint significance using an  $F$  test that compares the restricted (here:  $\rho_1 = \rho_2 = 0$ ) and unrestricted models.

$$F_{q, n-p} = \frac{(\text{SSE}_r - \text{SSE}_u) / q}{\text{SSE}_u / (n - p)}$$

where  $q$  is the number of restrictions and  $p$  is the number of parameters in our unrestricted model (include the intercept).

We can use the `waldtest()` function from the `lmtest` package for this test.

# Testing for autocorrelation

## Example: Approval ratings and oil prices

**Step 4:**  $F$  (or LM) test for  $\rho_1 = \rho_2 = 0$ .

```
# BG regression
bg_reg ← lm(
  e ~ lag(approve) + price_oil + lag(e) + lag(e, 2),
  data = approval_df
)
# Test significance of the lags using 'waldtest' from 'lmtest' package
p_load(lmtest)
waldtest(bg_reg, c("lag(e)", "lag(e, 2)"))
```

Here, we're telling `waldtest` to test

- the model we specified in `bg_reg` (our **unrestricted model**)
- against a model without `lag(e)` and `lag(e, 2)` (our **restricted model**)

# Testing for autocorrelation

## Example: Approval ratings and oil prices

**Step 4:**  $F$  (or LM) test for  $\rho_1 = \rho_2 = 0$ .

```
# BG regression
bg_reg <- lm(
  e ~ lag(approve) + price_oil + lag(e) + lag(e, 2),
  data = approval_df
)
# Test significance of the lags using 'waldtest' from 'lmtest' package
p_load(lmtest)
waldtest(bg_reg, c("lag(e)", "lag(e, 2)"))
```

```
#> Wald test
#>
#> Model 1: e ~ lag(approve) + price_oil + lag(e) + lag(e, 2)
#> Model 2: e ~ lag(approve) + price_oil
#>   Res.Df Df      F Pr(>F)
#> 1      57
#> 2      59 -2 1.6153 0.2078
```

# Testing for autocorrelation

Example: Approval ratings and oil prices

**Step 5:** Conclusion of hypothesis test

With a  $p$ -value of  $\sim 0.208$ , **we fail to reject the null hypothesis.**

- We cannot reject  $\rho_1 = \rho_2 = 0$ .
- We cannot reject "no autocorrelation".

# Testing for autocorrelation

## Example: Approval ratings and oil prices

**Step 5:** Conclusion of hypothesis test

With a  $p$ -value of  $\sim 0.208$ , **we fail to reject the null hypothesis.**

- We cannot reject  $\rho_1 = \rho_2 = 0$ .
- We cannot reject "no autocorrelation".

However, **we tested for a specific type of autocorrelation:** AR(2).

We might get different answers with different tests.

The  $p$ -value for AR(1) is 0.0896—suggestive of first-order autocorrelation.

# Living with autocorrelation

# Autocorrelation

## Working with it

Suppose we believe autocorrelation is present. What do we do?

# Autocorrelation

## Working with it

Suppose we believe autocorrelation is present. What do we do?

I'll give you three options.<sup>†</sup>

1. **Misspecification**
2. **Serial-correlation robust standard errors** (a.k.a. Newey-West)
3. **FGLS**

<sup>†</sup> You should take EC 422 to go much deeper into time-series analysis/forecasting.

# Autocorrelation

## Option 1: Misspecification

**Misspecification** with autocorrelation is very similar to our discussion with heteroskedasticity.

By incorrectly specifying your model, you can create autocorrelation.

Omitting variables that are correlated through time will cause your disturbances to be correlated through time.

# Autocorrelation

## Option 1: Misspecification

**Example:** Suppose births depend upon income and previous births

$$\text{Births}_t = \beta_0 + \beta_1 \text{Births}_{t-1} + \beta_2 \text{Income}_t + u_t$$

# Autocorrelation

## Option 1: Misspecification

**Example:** Suppose births depend upon income and previous births

$$\text{Births}_t = \beta_0 + \beta_1 \text{Births}_{t-1} + \beta_2 \text{Income}_t + u_t$$

but we write down the model as only depending upon previous births, *i.e.*,

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# Autocorrelation

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Note: This autocorrelation has nothing to do with  $u_t$ .

# Autocorrelation

## Option 2: Newey-West standard errors

As was also the case with heteroskedasticity, you can still estimate consistent standard errors (and inference) in the presence of autocorrelation.

These standard errors are called *serial-correlation robust standard errors* (or *Newey-West standard errors*).

We are not going to derive the estimator for these standard errors.

# Autocorrelation

## Option 3: FGLS

If we do not have a lagged outcome variable, then **feasible generalized least squares** (**FGLS**) can give us efficient and consistent standard errors.

# Autocorrelation

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Let's start with a simple static model that includes an AR(1) disturbance  $u_t$ .

$$\text{Births}_t = \beta_0 + \beta_1 \text{Income}_t + u_t \quad (1)$$

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And now subtract (4) from (2)...

# Autocorrelation

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$$\text{Births}_t - \rho \text{Births}_{t-1} = \beta_0 (1 - \rho) + \\ \beta_1 \text{Income}_t - \rho \beta_1 \text{Income}_{t-1} + \\ u_t - \rho u_{t-1}$$

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that happens to be **free of autocorrelation**.

# Autocorrelation

## Option 3: FGLS

This **transformed model** is free of autocorrelation.

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**Q:** How do we actually estimate this model? (We don't know  $\rho$ .)

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**Q:** How do we actually estimate this model? (We don't know  $\rho$ .)

**A:** FGLS (of course)...

1. Estimate the original (untransformed) model; save residuals.
2. Estimate  $\rho$ : Regress residuals on their lags (no intercept).
3. Estimate the **transformed model**, plugging in  $\hat{\rho}$  for  $\rho$ .

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