

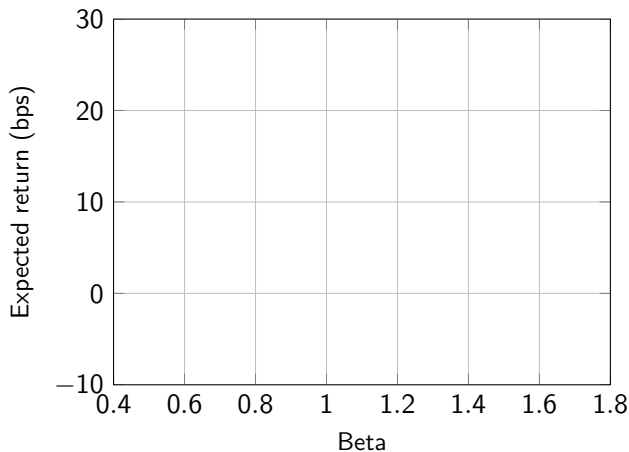
# **Asset Pricing on FOMC Announcements**

Julien Cujean (U of Bern)    Samuel Jaeger (U of Bern)

March 2023

# A few known facts regarding FOMC announcements

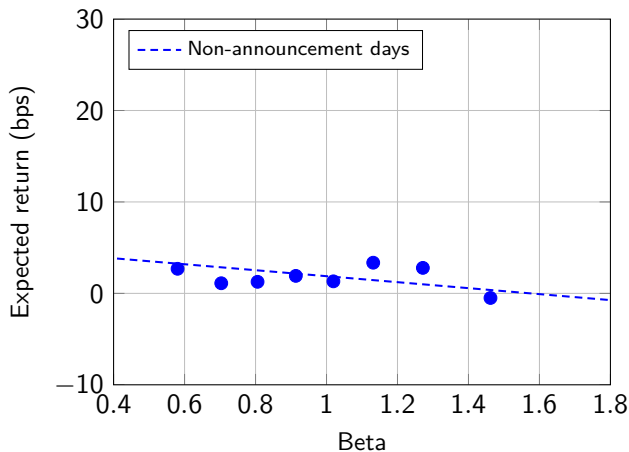
**fact 1.** CAPM works on announcements



**figure 1.** SML on A and NA days. Period: 2001-2022

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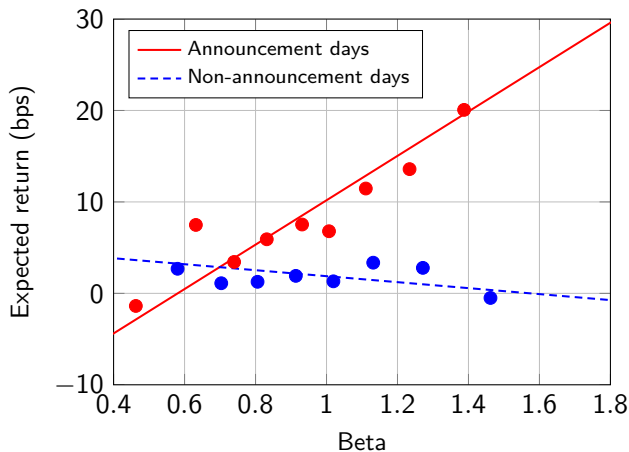
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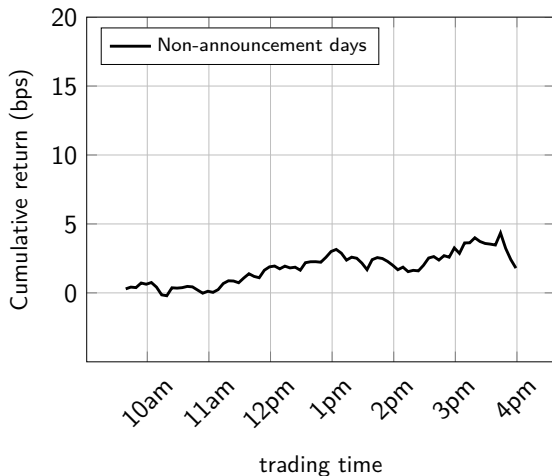
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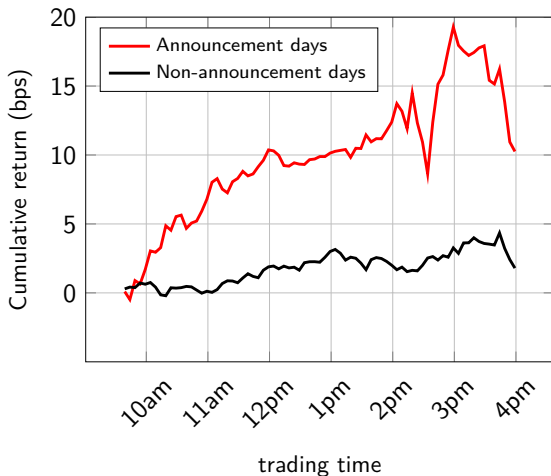
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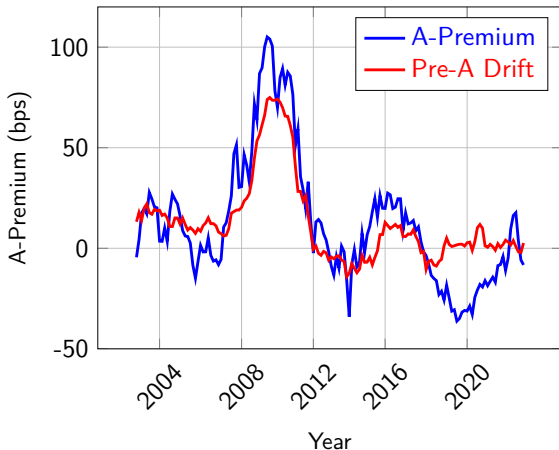
# A few known facts regarding announcements

**fact 3.** Pre- and post-A returns are unrelated

- ▶ The frequency at which pre-announcement returns “successfully predict” post-announcement returns is **46%**
- ▶ worse than a coin flip  $\Rightarrow$  low PI before the announcement.

# How facts changed in the last decade

1. The announcement premium has dropped and the drift is gone

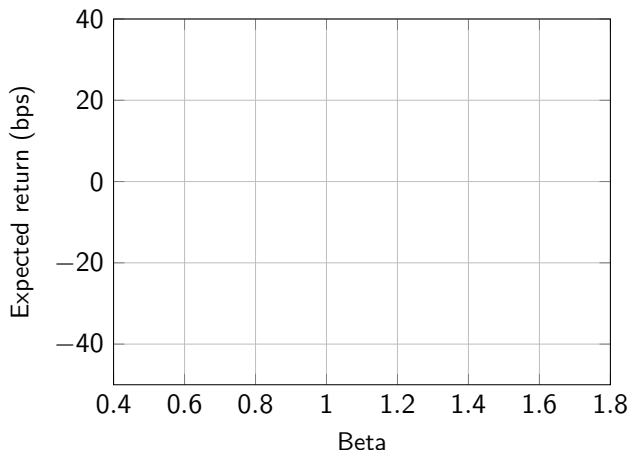


**figure 3.** Premium and Pre-A Drift over 2-year rolling windows.



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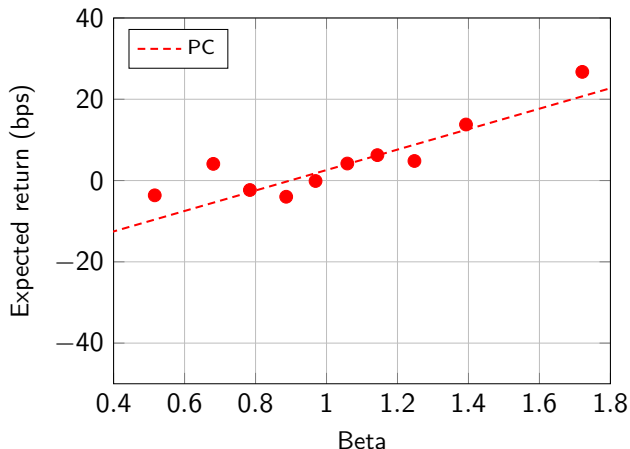
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**figure 4.** SML on PC and non-PC days. Period: 2011-2022

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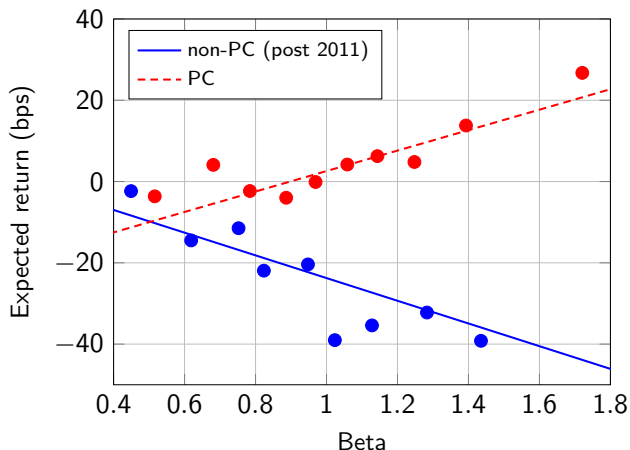
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- ▶ Right! and more problematically pre- and post-announcement returns are unrelated (Laarits, 2022)
- ▶ OK so we need other explanations (e.g., Ai and Bansal (2018); Wachter and Zhu (2021); Laarits (2022); Ai et al. (2022); Cocoma (2022))

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- ▶ Gee, the CAPM works on announcements (Savor and Wilson, 2014)
- ▶ Yeah, and betas become more compressed (Bodilsen et al., 2021; Andersen et al., 2021)

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- ▶ Why did the drift disappear (and may it reappear)?
- ▶ How are the facts related?

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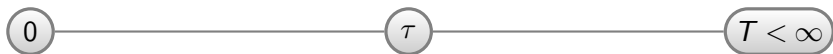
# This paper

- ▶ We push three ideas (theory + empirics):
  1. drift  $\Leftrightarrow$  information and can be switched on and off across equilibria
  2. but there is a complication: linking the drift to informativeness requires conditioning on good and bad news
  3. Exploiting the difference in asset-pricing implications across equilibria:
    - rise in noise in last decade  $\Rightarrow$  equilibrium shift  $\Rightarrow$  change in the facts
    - likely unrelated to the Fed's improved guidance

# Model

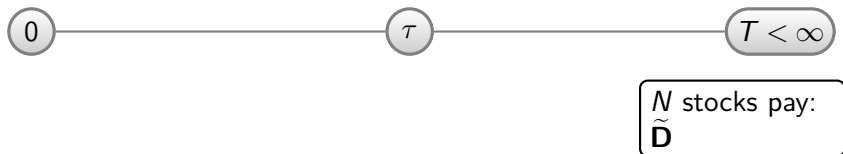
# Model

Continuous trading on  $[0, T)$



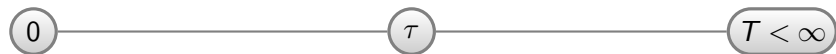
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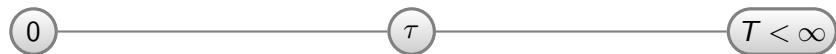
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$$\underbrace{\begin{pmatrix} \tilde{D}_1 \\ \vdots \\ \tilde{D}_N \end{pmatrix}}_{\tilde{\mathbf{D}}} = \underbrace{\begin{pmatrix} \phi_1 \\ \vdots \\ \phi_N \end{pmatrix}}_{\boldsymbol{\phi}} \tilde{F} + \underbrace{\begin{pmatrix} \tilde{\epsilon}_1 \\ \vdots \\ \tilde{\epsilon}_N \end{pmatrix}}_{\tilde{\boldsymbol{\epsilon}}}$$



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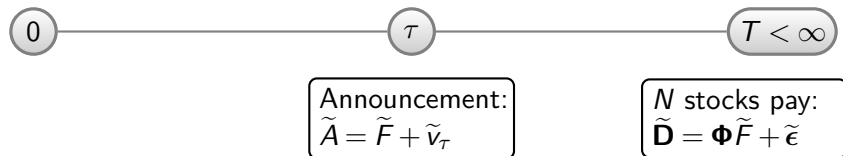


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0

agent  $i \in [0, 1]$ :  
 $\tilde{V}_0^i = \tilde{F} + \tilde{v}^i$

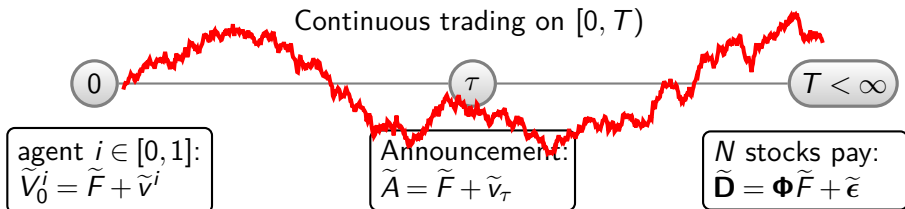
$\tau$

Announcement:  
 $\tilde{A} = \tilde{F} + \tilde{v}_\tau$

$T < \infty$

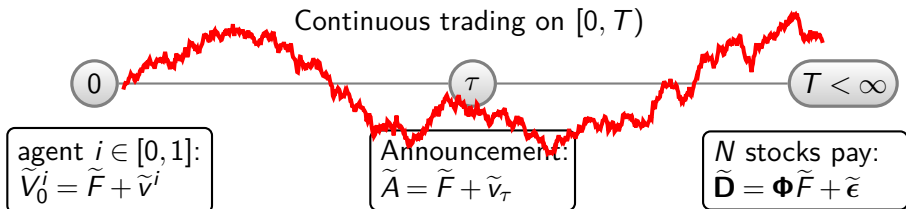
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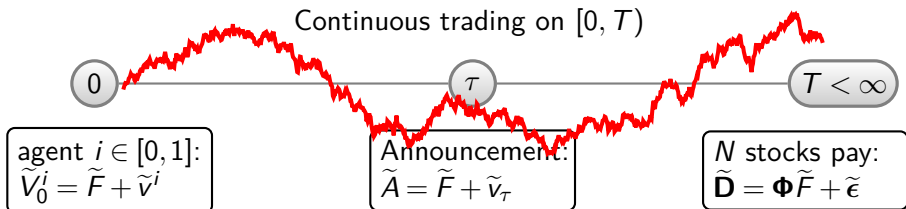
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Total number of shares of stocks **M** (the **market portfolio**)

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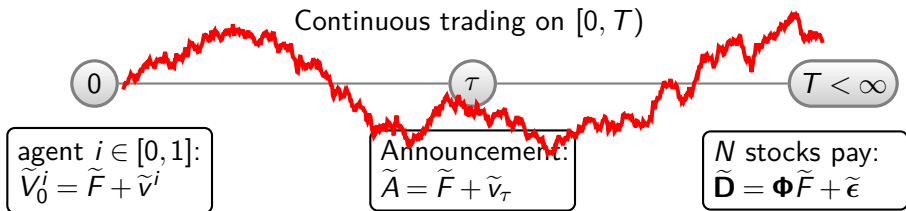
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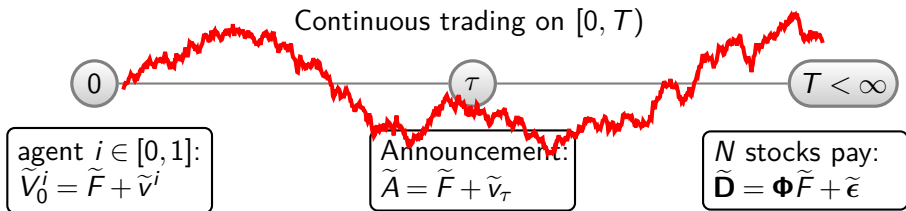
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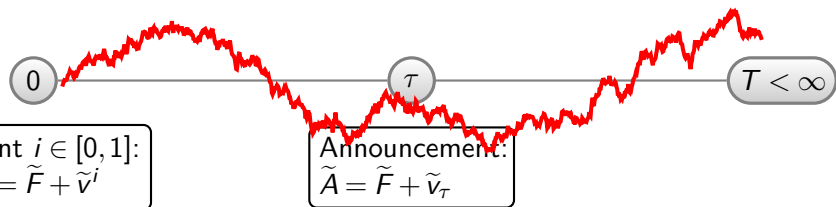
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agents have CARA= $\gamma$  utility over  $\tilde{W}_T^i$  and all innovations are normal, independent with precision  $\tau$ .



# Discussion



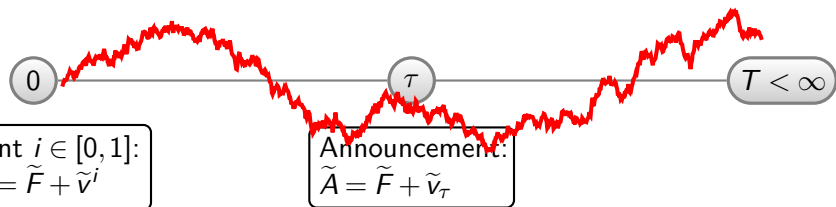
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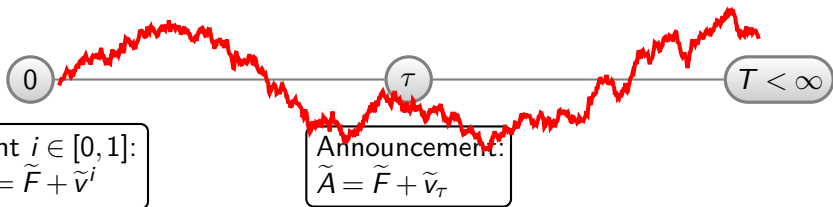
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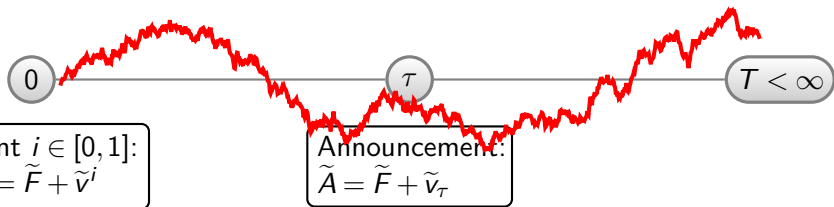
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estimate of  $\tilde{F}$  based on empiricist's data  $\mathcal{F}_t^c = \{\text{history of prices+ann.}\}$

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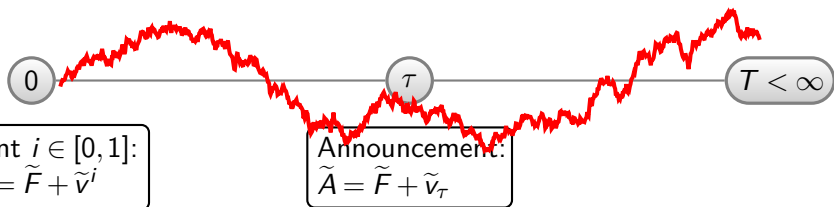
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$$\Rightarrow \xi_{0,t} \equiv \xi_t$$

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- $\alpha_t \equiv \frac{\tau_t - \tau_t^c}{\tau_t}$  optimal Bayesian weight on private info

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- $\alpha_t \equiv \frac{\tau_t - \tau_t^c}{\tau_t}$  optimal Bayesian weight on private info
- $\alpha \neq \lambda$  need not coincide (Cespa and Vives, 2012), which creates a relative **wedge**:

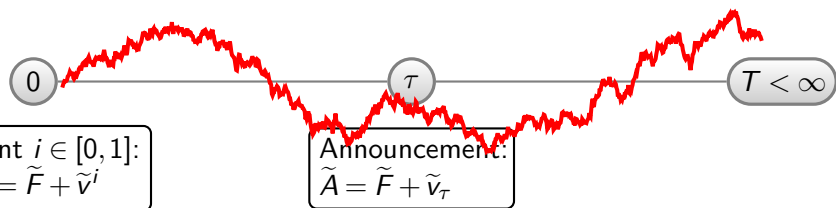
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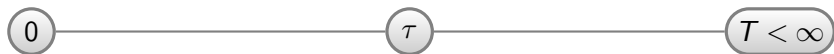
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agent  $i \in [0, 1]$ :  
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Announcement:  
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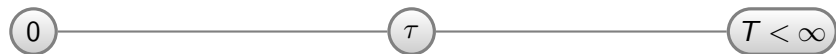
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**Lemma 1.** There always exists a **no-trade** equilibrium with  $\ell_t \equiv 0$  and:

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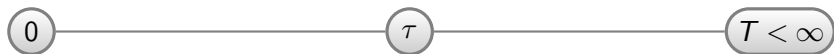


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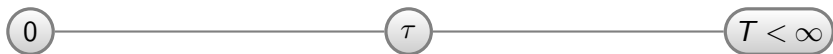
**discrete** amount of news  
(Wachter and Zhu, 2021)

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# Discussion



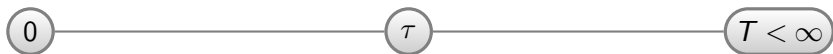
**discrete** amount of news  
(Wachter and Zhu, 2021)

Announcement:

$$\tilde{A} = \tilde{F} + \tilde{v}_\tau$$

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# Discussion



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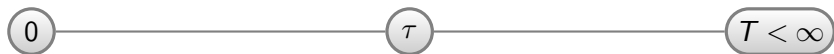
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# Discussion



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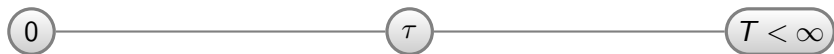
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# Two equilibria



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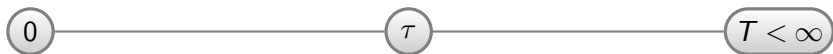
$A \Rightarrow$  **no-trade**  $\tau_G=0$  or  $\tau_G=\infty$  **fully-revealing** ( $\text{cov}(\Delta P)$  noninvertible).

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# Two equilibria



Announcement:  
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discrete amount of noise

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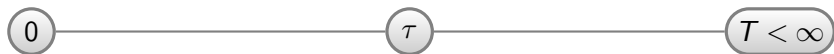
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## Two equilibria



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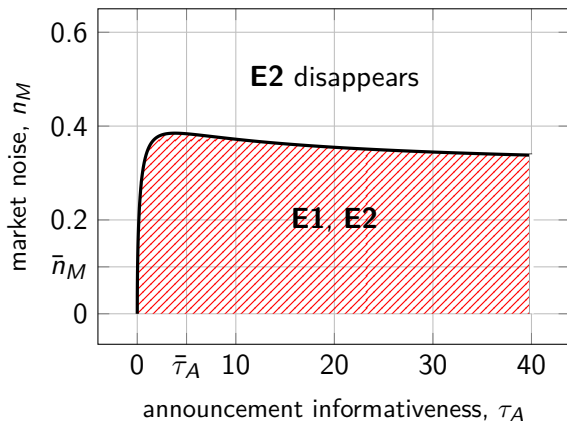
**E1 low**  $\tau_G$  eqm. weak speculation + drift.

**E2 high**  $\tau_G$  eqm. strong speculation + drift.

## Two equilibria

Announcement is summarized by two parameters:

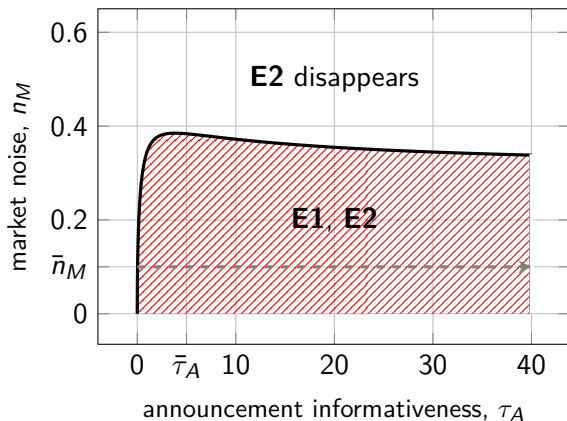
1. its informativeness,  $\tau_A$
2. how much market noise comes with it,  $n_M$



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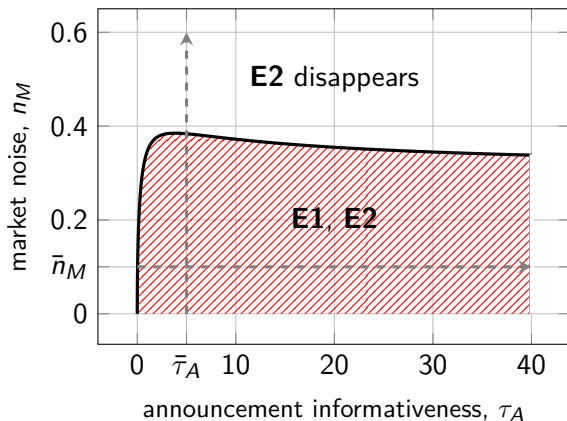
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## Two equilibria

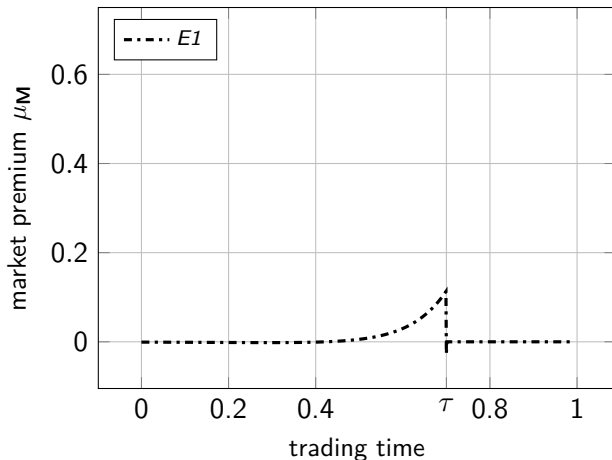
Announcement is summarized by two parameters:

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## Prediction 1. switching the drift on and off

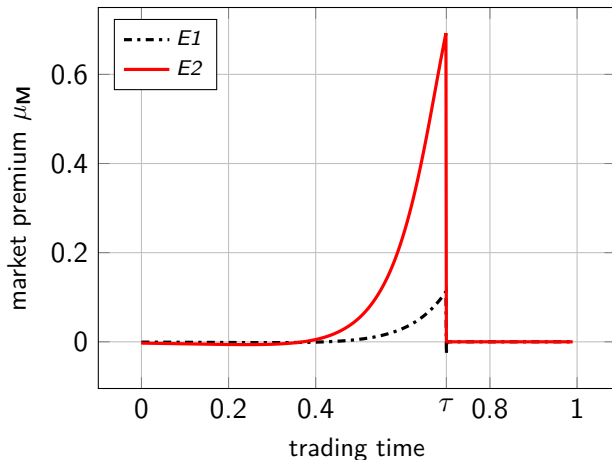
Resolution of uncertainty (Epstein and Turnbull (1980)) in the form of PI commands a premium:





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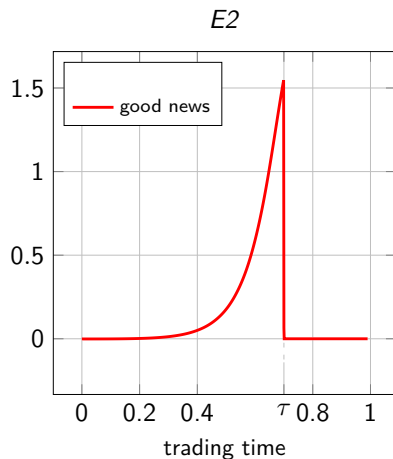
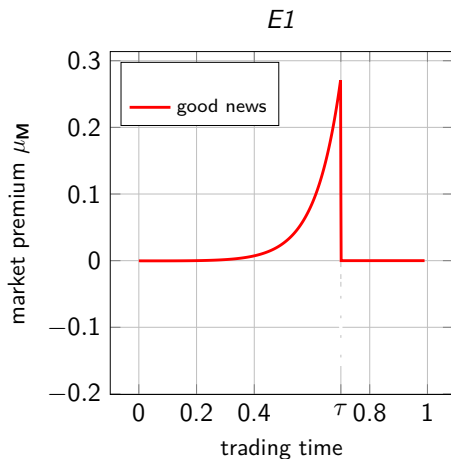


## Prediction 2. Asymmetry across good and bad news

Epstein and Turnbull (1980)'s mechanism is nondirectional, hence there must be an asymmetry across good and bad news:

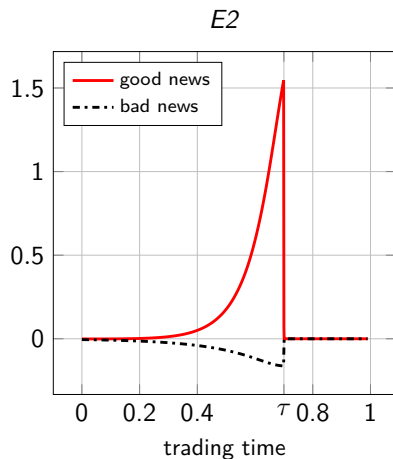
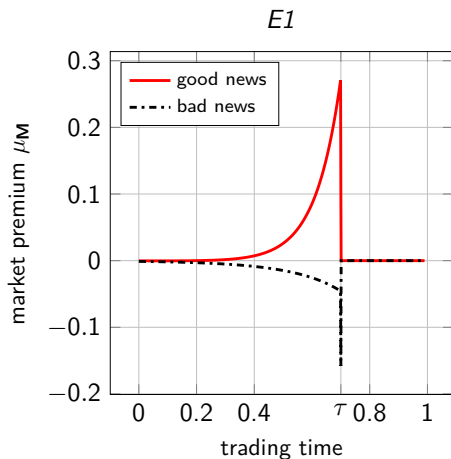
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# Beta formulation

CAPM fails at all dates (except at the close) due to **noise**:

$$\mu(\sigma_{\mathbf{M}}, \mu_{\mathbf{M}}; n.) = -\frac{n.^2 \tau_{\epsilon} / N}{\sigma_{\mathbf{M}}^2 - n.^2 \tau_{\epsilon} / N} \mu_{\mathbf{M}} \mathbf{1} + \frac{\sigma_{\mathbf{M}}^2 \mu_{\mathbf{M}}}{\sigma_{\mathbf{M}}^2 - n.^2 \tau_{\epsilon} / N} \beta(\sigma_{\mathbf{M}}; n.)$$

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$$\beta(\sigma_M; n.) = \frac{1}{\sigma_M^2} ((\sigma_M^2 - n.^2 \tau_\epsilon / N) / \bar{\Phi} \Phi + n.^2 \tau_\epsilon / N \mathbf{1})$$

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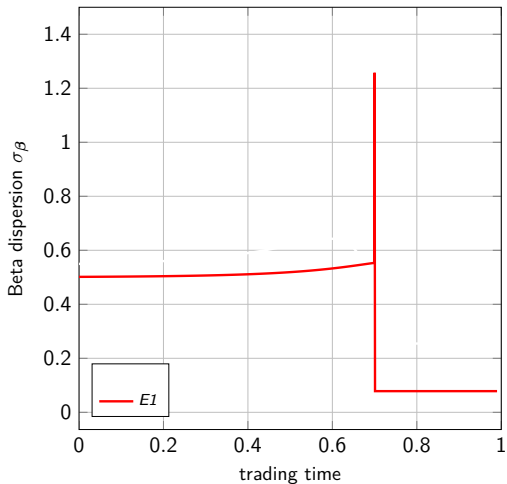
$$\beta(\sigma_{\mathbf{M}}; n.) = \frac{1}{\sigma_{\mathbf{M}}^2}((\sigma_{\mathbf{M}}^2 - n.^2\tau_{\epsilon}/N)/\bar{\Phi}\Phi + n.^2\tau_{\epsilon}/N\mathbf{1})$$

Two scenarios depending on noise:

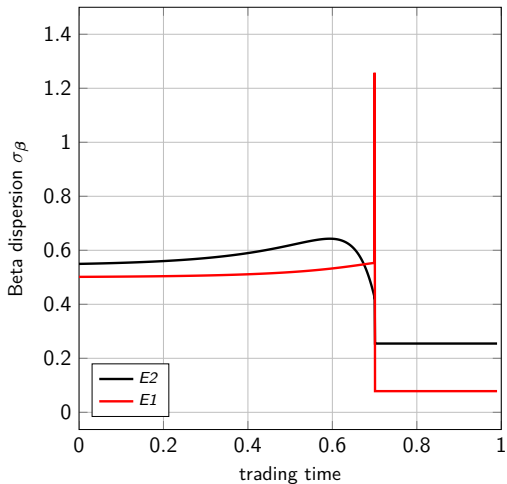
- ▶ ***n.*** large: SML is downward-sloping
- ▶ ***n.*** small: CAPM works “too well”



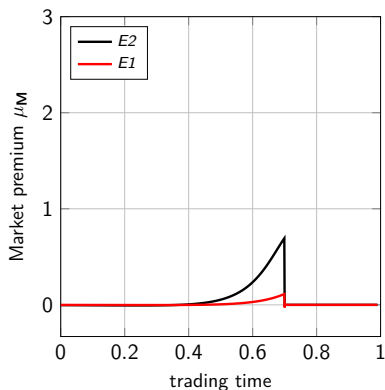
Pred 3. beta dispersion moves in opposite ways for low  $n$



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## Prediction 4. the CAPM works “too well”

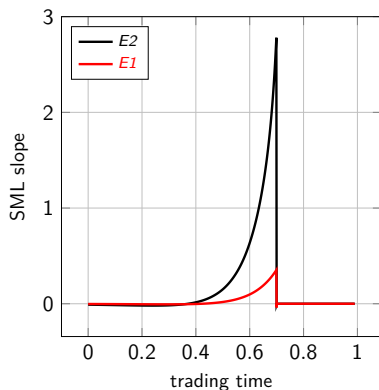
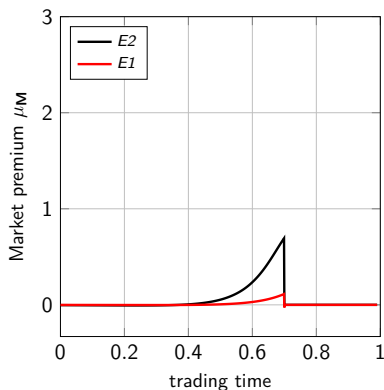


Beta-return relation:

$$\mu(\sigma_M, \mu_M; \tau) = -\frac{n^2 \tau_\epsilon / N}{\sigma_M^2 - n^2 \tau_\epsilon / N} \mu_M \mathbf{1} + \frac{\sigma_M^2 \mu_M}{\sigma_M^2 - n^2 \tau_\epsilon / N} \beta(\sigma_M; \tau)$$

$$\beta(\sigma_M; \tau) = \frac{1}{\sigma_M^2} ((\sigma_M^2 - n^2 \tau_\epsilon / N) / \bar{\Phi} \Phi + \tau^{-1} \gamma^2 \tau_\epsilon / N \mathbf{1})$$

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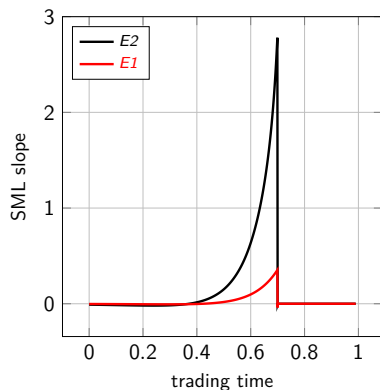
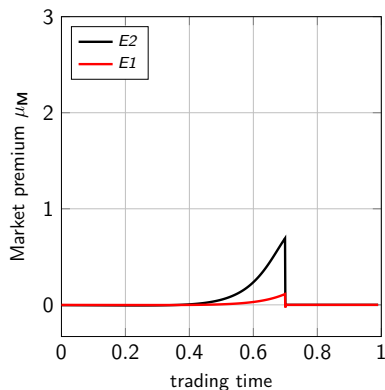


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## Prediction 4. the CAPM works “too well”



We can rewrite the SML slope as:

$$\text{SML Slope} = \frac{\sigma_{\Phi}/\bar{\Phi}}{\sigma_{\beta}} \mu_M$$

where  $\sigma_{\beta}$  denotes beta dispersion and  $\sigma_{\Phi}/\bar{\Phi}$  dispersion in value

# Testing the model predictions

- ▶ **Main data source:** NYSE TAQ database
- ▶ **Sample period:** Jan 2001–Dec 2022, sampled every 5 minutes
- ▶ **Stock universe:** S&P500 stocks traded on NYSE (370 stocks).
- ▶ **FOMC announcements:** 2pm and 2.15pm announcements (167 announcements)

# Testing the model predictions

- ▶ **Press conferences (PCs):** introduced in April 2011, are "intended to further enhance the clarity and timeliness of the Federal Reserve's monetary policy communication" (Federal Reserve, 2011)
- ▶ Improved forward guidance and/or potential changes in market noise at the announcement might have triggered an equilibrium shift
- ▶ The literature has shown differences in asset-pricing patterns on PC days (Bodilsen et al. (2021), Boguth et al. (2019))
- ▶ **Two subsamples:**
  - ▶ non-PC days: January 2001–May 2018 (112 observations) <sup>1</sup>
  - ▶ PC days: April 2011–December 2022 (55 observations)

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<sup>1</sup>Between 2011 and 2018, PCs took place only every 2nd time. After that they were systematically introduced for each announcement.

# Good news vs. bad news

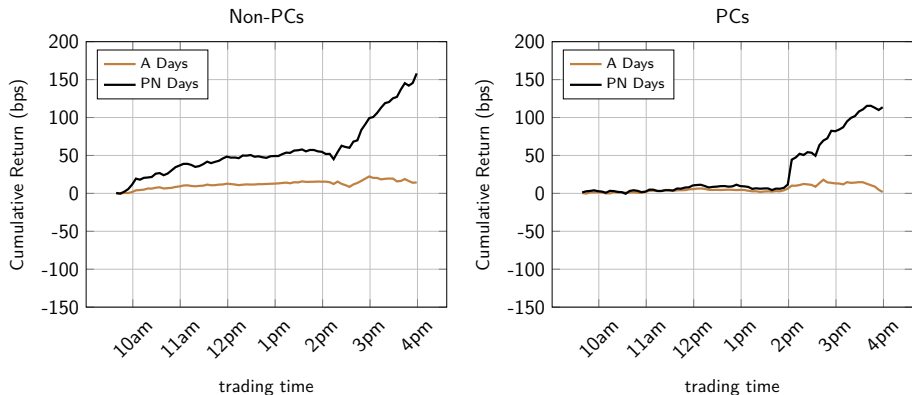
- ▶ Key to distinguish between “positive” (PN) and “negative” (NN) announcement outcomes
- ▶ We define PN/NN based on returns over the day:
  - ▶ PN: Announcement days whose daily returns fall in upper 75% quintile of the distribution
  - ▶ NN: Announcement days whose daily returns fall in lower 25% quintile of the distribution



## Testing Predictions 1 and 2

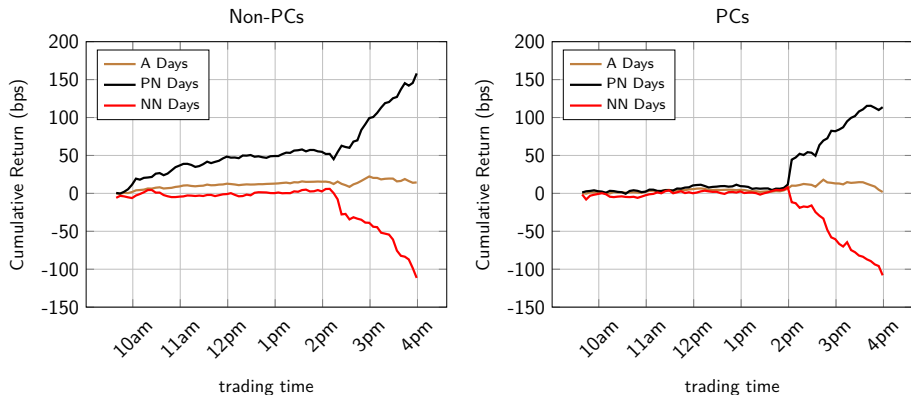
- ▶ **Prediction 1:** In **E1** prices are **less informative** and the premium is to a large extent realized at the announcement and in **E2** returns are more informative which generates a stronger pre-A **drift**.
- ▶ **Prediction 2:** By conditioning on “good” and “bad” news the drift on non-PC days and market reaction on PC days is much stronger on good news  $\Rightarrow$  informativeness concentrates on good news.

# Testing Predictions 1 and 2



**figure 5.** Average cumulative returns on non-PC and PC days

# Testing Predictions 1 and 2



**figure 5.** Average cumulative returns on non-PC and PC days

## Testing Predictions 1 and 2

- ▶ Price informativeness measure (PI) follows the idea of Weller (2017):

$$PI = \frac{R_{pre}}{R_{post}}$$

where  $R_{pre}$  is pre-announcement return and  $R_{post}$  the post-announcement return

- ▶ Positive values indicate that the market correctly anticipates the announcement outcome; negative values indicate the opposite
- ▶ We report the relative frequency of  $PI > 0$ , which we define as  $\Omega$
- ▶  $\Omega > 50\% \Rightarrow$  informative,  $\Omega = 50\% \Rightarrow$  uninformative

# Testing Predictions 1 and 2

	A-Days	PN Days	NN Days
		<b>Non-PC Days</b>	
Return (bps)	14.42 (1.35)	158.15*** (9.21)	-111.48*** (-8.64)
Pre-A Drift (bps)	15.66*** (3.44)	54.60*** (5.20)	4.50 (0.50)
$\Omega$	52.68	82.14	50.00
Observations	112	28	28
		<b>PC Days</b>	
Return (bps)	1.78 (0.15)	113.67*** (7.26)	-108.06*** (-8.85)
Pre-A Drift (bps)	6.30 (1.42)	11.60 (1.42)	8.03 (0.71)
$\Omega$	32.73	57.14	42.86
Observations	55	14	14

**Table 1.** Summary stats

# Testing Predictions 1 and 2

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**Table 1.** Summary stats

# Alternative explanations for the asymmetry

## 1. Difficulty in shorting the market

- ▶ Betting on NN requires short-selling, and costly short-selling could thus explain the asymmetry.
- ▶ We follow Lamont and Thaler (2003) and create a synthetic short position from ATM S&P 500 index options.
- ▶ We define implicit short-selling costs as the % deviation of the synthetic short from the S&P 500 index.

# Alternative explanations for the asymmetry

## 2. Asymmetry in the signal

- ▶ The Fed tends to conduct accommodating policies in bad times, but does not systematically tighten policies in good times
- ▶ This “Fed put” (Cieslak and Vissing-Jorgensen, 2020) comes without a corresponding “Fed call”, which may create an asymmetry across positive and negative news.
- ▶ Negative past returns could be taken as a signal for easing policies  $\Rightarrow$  we control for this with a dummy (1 if prev cycle return  $< 0$ , 0 otherwise)



## Alternative explanations for the asymmetry in the drift

	(3)	(4)	(5)
<i>Intercept</i>	32.11*** (11.53)	-4.54 (22.11)	17.22 (22.37)
<i>FedPutSignal</i>	16.30* (19.14)		
<i>VIX</i>		1.87* (1.06)	
<i>ShortSellingCosts</i>			0.67 (0.44)
R-squared	0.02	0.13	0.1
Numb. of Announcements	42	42	40

**Table 2.** Drivers of pre-announcement returns (dependent variable) on **PN days**.  
Extract from the original table in the paper.

## Alternative explanations for the asymmetry in the drift

	(3)	(4)	(5)
<i>Intercept</i>	-9.66 (6.15)	-45.67*** (16.34)	-4.00 (13.63)
<i>FedPutSignal</i>	42.93*** (15.56)		
<i>VIX</i>		2.37*** (0.83)	
<i>ShortSellingCosts</i>			0.18 (0.4)
R-squared	0.21	0.28	0.02
Numb. of Announcements	42	42	38

**Table 3.** Drivers of pre-announcement returns (dependent variable) on **NN days**. Extract from the original table in the paper.

## Testing Prediction 3

- ▶ **Prediction 3:** Beta dispersion close to and at the announcement moves in opposite directions across equilibria for low noise, with betas sharply moving apart in E1, although beta compression is systematic post-announcement

## Testing Prediction 3

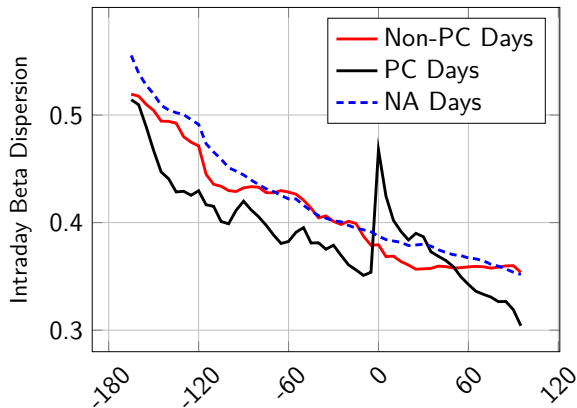
- ▶ We follow Andersen et al. (2021) and Bodilsen et al. (2021) in estimating betas
- ▶ First, we estimate intraday betas at the stock level

$$\beta_i = \frac{\sum_{i=1}^{n_c} R_i R_m}{\sum_{i=1}^{n_v} R_m^2}$$

- ▶ Second, we create ten value-weighted beta-sorted portfolios  $p = \{1, 2, \dots, 10\}$  every day and then estimate the betas of these portfolios
- ▶ Finally, we estimate beta dispersion as:

$$\sigma_{\beta}^2 = \sqrt{\frac{1}{10} \sum_{p=1}^{10} (\beta_p - 1)^2}$$

## Testing Prediction 3



**figure 6.** Intraday beta dispersion

## Testing Prediction 4

- ▶ **Prediction 4:** The CAPM works “too well” or on the contrary the SML and the market go in opposite directions. Excess SML slope is entirely explained by dispersion in beta and in value.
- ▶ We focus on the scenario whereby the SML slope and the market return have the same sign (129 announcements)
- ▶ To estimate SML slope, we run Fama and MacBeth (1973) regressions

## Testing Prediction 4

	A-Days	PC Days	Non-PC Days
Intercept	-13.01 (-1.63)	-22.59 (-1.67)	-8.22 (-0.83)
Slope	26.97* (1.72)	25.17 (1.10)	27.87 (1.35)
Excess Slope	46.00*** (6.59)	49.92*** (4.23)	44.03*** (5.07)
Avrg Beta Disp	0.37	0.34	0.39
Observations	129	43	86

**Table 4.** Excess Slope

## Testing Prediction 4

	A-Days	PC Days	Non-PC Days
Intercept	-13.01 (-1.63)	-22.59 (-1.67)	-8.22 (-0.83)
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Excess Slope	<b>46.00***</b> (6.59)	<b>49.92***</b> (4.23)	<b>44.03***</b> (5.07)
Avrg Beta Disp	0.37	0.34	0.39
Observations	129	43	86

**Table 4.** Excess Slope



## Testing Prediction 4

- ▶ In the model, excess slope is entirely explained by the ratio between dispersion in value to dispersion in beta.
- ▶ Andrei et al. (2019) show that the vector  $\Phi$  is equivalent to market-to-book ratios and calculate dispersion in value as:

$$\frac{\sigma_{\Phi}}{\bar{\Phi}} \approx \frac{\sigma_{B/M}}{|B/M|}.$$

- ▶ We regress excess slope on the ratio between dispersion in value to dispersion in betas:

$$\text{Ratio} \equiv \frac{\sigma_{\Phi}/\bar{\Phi}}{\sigma_{\beta}}.$$

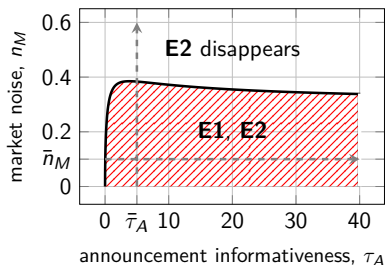
## Testing Prediction 4

	A Days (1)	PC Days (2)	non-PC Days (3)
Constant	-17.60 (-0.77)	-50.10 (-1.31)	-12.06 (-0.43)
Ratio	<b>80.17***</b> (2.61)	<b>111.15**</b> (2.41)	<b>75.79*</b> (1.83)
R-squared	0.20	0.19	0.21
Observations	129	43	86

**Table 5.** Excess slope and dispersion in beta and value

# Market noise and the introduction of PCs

- ▶ Asset-pricing implications seem to differ across the PC and non-PC samples the same way they do across equilibria **E1** and **E2**.
- ▶ Furthermore, we have shown that **E2** disappears as market noise rises.



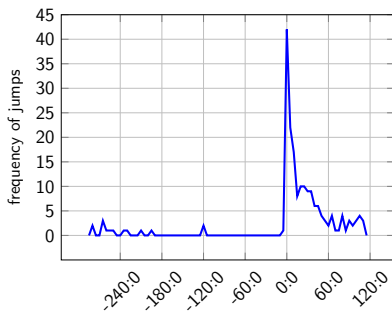
- ▶ Therefore, it is possible that the apparent shift from **E2** to **E1** is in fact unrelated to the introduction of PCs but rather that market noise rose in the period following their introduction

## Market noise and the introduction of PCs

- ▶ Market reaction to the announcement represents a return discontinuity (“a jump”)
- ▶ Following Mancini (2001, 2009), we define a jump as an increment in returns that exceeds the threshold level:

$$v_{t_M} = 3\sqrt{BV_{t,n}^M n^{-0.47}},$$

where  $BV_{t,n}^M$  denotes the bipower variation (Barndorff-Nielsen and Shephard, 2004) of the market portfolio  $M$  on day  $t$



# Market noise and the introduction of PCs

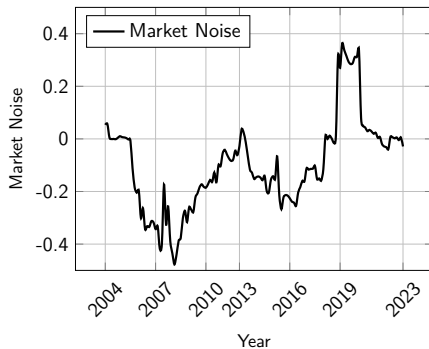
- ▶ Jumps contain fundamental information (a permanent component) and noise (a transitory component)
- ▶ We want to disentangle the transitory part,  $n_M$ , from information; we follow the idea of Boguth et al. (2022) and run:

$$R(t_{open}, (t+1)_{close}) = \alpha + \beta R(t_{open}, t_{announcement-1min}) + \epsilon_t,$$
$$R(t_{open}, (t+1)_{close}) = \alpha + \beta R(t_{open}, t_{announcement+30min}) + \epsilon_t.$$

- ▶ We measure noise  $n_M$  as the  $\Delta$  between the  $R^2$ s of the two regressions:

$$\text{market noise} \equiv -(R_{post}^2 - R_{pre}^2) = -\Delta R^2 \approx n_M$$

# Market noise and the introduction of PCs



**figure 7.** Market noise over time

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