Managing Policy Preannouncement

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Road map

WSJ Powell Still Sees Room for the Fed to Cut Rates This Year

Stronger-than-anticipated economic activity this year hasn't changed the Federal Reserve's broad expectation that declining inflation will allow for interest-rate cuts this year, Chair Jerome Powell said Wednesday.

Powell pointed to signs that labor-market conditions are less tight than they have been in recent years, a view that has eased concerns that paychecks and prices might rise in tandem.

Meanwhile, signs of firmer-than-expected inflation in January and February haven't shaken the Fed's stance that price growth will continue to slow down despite some bumps, Powell said at a conference in Stanford, Calif.

"The recent data do not...materially change the overall picture, which continues to be one of solid growth, a strong but rebalancing labor market, and inflation moving down to 2% on a sometimes bumpy path," he said.

Figure 1: Preannouncement's importance.

- How do governments adjust preannouncement?

Table 1: Examples of Policy Preannouncement: A Stylized Overview.

Country	Policy	Anticipated to	Announcement date	Implementation date
U.S.	The American Rescue Plan Act of 2021.	Expire	Mar. 11, 2021.	Dec. 31, 2021.
	The Infrastructure Investment and Jobs Act.	Expire	Nov. 15, 2021.	Dec. 31, 2025.
E.U.	Net asset purchases and interest rates rises of ECB.	Roll out	Jun. 9, 2022.	Jul 1, 2022 and Sep. 1, 2022.
	Digital Services Tax.	Roll out	Dec. 15, 2020.	Jan. 1, 2023.
China	VAT reduction extension for small enterprises.	Expire	Jan. 9, 2023.	Dec. 31, 2023.
	Tax holiday of NEVs.	Expire	Sep. 18, 2022.	Dec. 31, 2023.
India	Electronics manufacturing incentive scheme.	Roll out	Feb. 1, 2021.	Mar. 1, 2021.
Japan	Go To Travel Campaign.	Expire	Jul. 2020.	Sep. 6, 2020.

Past debates concentrate on giving preannouncement or not.

- Pros
  - Reduce volatility.
    - Bernanke et al. (2007); Hazell et al. (2022)
  - Enhance policy effectiveness
    - House and Shapiro (2006); Bali et al. (2019)
  - ...
- Cons
  - Lead to speculation.
    - De Long et al. (1990); Lepetyuk et al. (2021)
  - Reduce the effectiveness of policy.
    - Lucas (1973); Sargent and Wallace (1975); Allen et al. (2022)
  - ...

Does the preannouncement length matter for welfare concerns?

- Option value theory
  - The more the better for rational agents.
- Recent counterexamples show agents are not as rational as we expect.
  - Households are not perfectly rational because of **friction**. (De Tocqueville, 1850; Best and Kleven, 2018)
  - People tend to **forget** the policy deadline as preannouncement length increases. (Altmann et al., 2022)
  - **Reminds** can enhance welfare. (Karlan et al., 2016)

- We highlight that preannouncement length influences households' welfare in two opposite ways.
  - **Limited memory effect.**
    - Due to cognitive constraints.
    - Miss the deadline at extreme case.
  - **Option value effect.**
    - From information advantage.
    - Marginal gain decrease in preannouncement length.
- A **balance** between the two forces will yield an optimal time to release preannouncement.

- We utilizes changes in vehicle purchase tax rate of China's auto industry to study the policy implication of preannouncement management.
- Advantages of our setting
  - The tax rate has both preannounced and abrupt variations.
    - 1 exogenous tax cut, 2 preannounced tax rises.
    - Help to distinguish memory limitation from price elasticity.
  - Representativeness.
    - China has the largest auto market.
    - The finding is referable to other policies both in China and other countries.
  - Access to administrative data.
    - Monthly transaction level data.

- We build a theoretical framework to model how limited memory influence individual's purchase decision.
  - Dynamic discrete choice model.
  - Option value effect.
    - Generated by price elasticity and Markov preannouncement.
  - Limited memory effect.
    - Generated by memory limitation parameter and preannouncement length.
- We prove that there exists an unique optimal time to release pre-announcement.
- The model is then estimated via SMM. Our model outperforms than candidates like present bias model.
- We also empirically find that the optimal time to release preannouncement is 2 months in advance.

Literature

- We first contribute to the literature studying behavioral bias and policy effect.
  - Present bias and monetary policy efficiency.
    - Laibson et al. (2021)
  - Optimal taxation.
    - Allcott et al. (2019); Farhi and Gabaix (2020)
- **We highlight preannouncement management as a new policy tool to enhance policy efficiency.**
- A carefully designed preannouncement length can enhance households' welfare by balancing option value effect and limited memory effect.

- Our findings also contribute to the literature that theoretically analyzes how behavioral bias influence people's reactions to deadlines.
  - Cognitive constraints (Taubinsky, 2013; Altmann et al., 2022)
  - Present bias (O'Donoghue and Rabin, 1999)
  - Or the interplay between the two (Ericson, 2017)
- We complement their analysis by
  - **Embedding the limited memory effect into a dynamic discrete choice** model which is more general in empirical IO applications.
  - Proving that there's a unique optimal time to release preannouncement to minimize the probability of missing deadline.
  - Providing empirical evidence for the importance of preannouncement management.

- Finally, our findings offer a valuable contribution to the field of tax misperception.
- Past issues studied in this field cover only static cases.
  - failing to account for taxes not reflected in posted prices (Chetty et al., 2009)
  - using average tax rates instead of marginal tax rates (Taubinsky and Rees-Jones, 2018; Rees-Jones and Taubinsky, 2020)
  - or relying on heuristics like rounding (Conlon and Rao, 2020)
- **Our work innovatively extends this analysis into intertemporal settings.**

Policy background

- In October 2015, China halved the vehicle purchase tax to 5 percent for small-displacement vehicles (with cylinder capacity $\leq$ 1.6L).
- On December 13, 2016, the tax rate on small displacement vehicles was announced to rise to 7.5% throughout the year 2017 and eventually return to 10% on January 1, 2018.

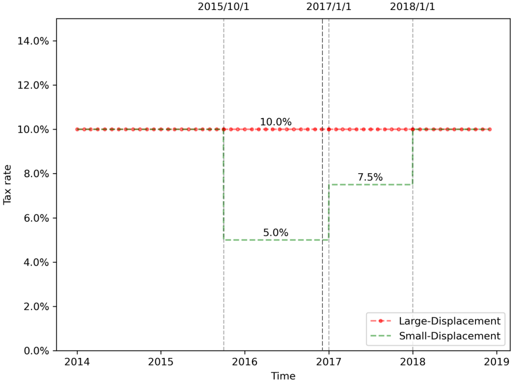


Figure 2: Vehicle purchase tax change

Demand part

- In this section we utilize the dynamic discrete choice model to capture the dynamic durable goods purchase decision. (Rust, 1987; Gowrisankaran and Rysman, 2012; Liu et al., 2020)
- Specifically, there are $i = 1, \ldots, I$ households and $j = 1, \ldots, J$ vehicles in a market c.
- Flow utility is formed in rational way, whereas discounted expected utility from future is mis-estimated by households due to limited memory.

Flow utility

- The flow utility of household i of ownership status k who purchases model j at time t is assumed to take the form

$$u^k_{i,j,t} = \underbrace{\alpha p_{j,t} + \sigma^p p_{j,t} v^p_i + \pi y_{i,t} p_{j,t}}_{\varsigma_{i,j,t}} + \underbrace{f(t) + \lambda_j + \xi_{j,t}}_{\Lambda_{j,t}} + \underbrace{\sigma^c v^c_i}_{\vartheta_i} + \varepsilon_{i,j,t}, \tag{1}$$

  - $p_{j,t}$ is price, v^p_i is household level heterogeneous price sensitivity, y_i is household income. $\varsigma_{i,j,t}$ hence covers all price associated utility terms.
  - $f(t)$ is the preference trend, λ_j is model fixed effects, $\xi_{j,t}$ is the error term unexplained by the model. $\Lambda_{j,t}$ captures utility homogeneous among vehicles.
  - v^c_i captures heterogeneity in willingness to pay for a car. ϑ_i carries heterogeneous WTP.
  - $\varepsilon_{i,j,t}$ is idiosyncratic taste shock following type I extreme value distribution.

- and when i not to purchase vehicle at t,

$$u_{i,0,t}^{k} = \underbrace{\lambda_k + f(t) + \xi_{k,t}}_{\Lambda_{k,t}} + \underbrace{\sigma^c v_i^c}_{\vartheta_i} + \varepsilon_{i,k,t}. \tag{2}$$

Expected utility

- Define the expected utility conditional on state variables of preference D_i, information set $I_{i,t}$ as a Bellman equation represented below

$$EV_{t+1}(D_{i,t+1}, k_{i,t+1}, I_{i,t+1}) =$$
$$\mathbf{E}_{\varepsilon_{i,t+1}}\left[\max_{j=0,1,\ldots,J_t}\left\{u_{i,j,t}^{k_{i,t+1}} + \beta\mathbf{E}[EV_{t+2}(D_{i,t+2}, k_{i,t+2}, I_{i,t+2})|D_{i,t+1}, k_{i,t+1}, I_{i,t+1}]\right\}\right] \quad (3)$$

- Let $\widetilde{I}_{i,t}$ be the information set when households were completely not aware of future tax rises, define the corresponding expected utility as

$$\widetilde{EV}_{t+1}(D_{i,t+1}, k_{i,t+1}, \widetilde{I}_{i,t+1}) =$$
$$\mathbf{E}_{\varepsilon_{i,t+1}}\left[\max_{j=0,1,\ldots,J_t}\left\{u_{i,j,t}^{k_{i,t+1}} + \beta\mathbf{E}[\widetilde{EV}_{t+2}(D_{i,t+2}, k_{i,t+2}, \widetilde{I}_{i,t+2})|D_{i,t+1}, k_{i,t+1}, \widetilde{I}_{i,t+1}]\right\}\right] \quad (4)$$

Decision utility under limited memory

- Inclusive value sufficiency assumption (Gowrisankaran and Rysman, 2012 JPE):
  - $\delta_{i,t}$ the expected utility conditional on purchasing is the sufficient statistics to forecast future status.

$$\delta_{i,t} = \mathbf{E} \max_{j=1,\ldots,J} \{u_{i,j,t}^{k_{i,t}} + \beta \mathbf{E}[EV_{t+1}(D_{i,t+1}, k_{i,t+1} = j, I_{i,t+1}) | D_{i,t}, k_{i,t}, I_{i,t}]\}. \tag{5}$$

  - $\delta_{i,t}$ follows first order Markov process. And $I_{i,t}$ can be replaced by $\delta_{i,t}$.
  - We make such assumption on the expected utility in the case of no preannouncement, $\widetilde{\delta}_{i,t}$, as well.
- Limited memory assumption (Karlan et al., 2016 MS):
  - Affected by limited memory, households' instantaneous utility is a convex combination between the rational EV and the no preannouncement $\widetilde{EV}$. Hence their decision utility function for outside option is

Transformation of demand problem

- Under prior assumptions, we can write $\delta_{i,t}$, $EV(D_i, j, \delta_{i,t})$, $\tilde{\delta}_{i,t}$ and $\widetilde{EV}(D_i, j, \tilde{\delta}_{i,t})$ in contract mapping form.

$$\delta_{i,t} = \ln(\sum_{j=1,\dots,J_t} \exp(\Lambda_{j,t}^{k_{i,t}} + \vartheta_i + \varsigma_{i,j,t} + \beta \mathbf{E}[EV_{t+1}(D_{i,t+1}, k_{i,t+1} = j, \delta_{i,t+1}) | D_{i,t}, k_{i,t}, \delta_{i,t}])) \tag{6}$$

$$EV_{t+1}(\delta_{i,t+1}, k_{i,t+1}) =$$
$$\ln(\exp(\delta_{i,t+1}) + \exp(\Lambda_{0,t+1}^{k_{i,t+1}} + \vartheta_i + \beta \mathbf{E}[EV_{t+2}(\delta_{i,t+2}, k_{i,t+2} = k_{i,t+1}) | \delta_{i,t+1}, k_{i,t+1}])). \tag{7}$$

$$\widetilde{\delta}_{i,t} = \ln(\sum_{j=1,\dots,J_t} \exp(\Lambda_{j,t}^{k_{i,t}} + \vartheta_i + \varsigma_{i,j,t} + \beta \mathbf{E}[EV_{t+1}(D_{i,t+1}, k_{i,t+1} = j, \widetilde{\delta}_{i,t+1}) | D_{i,t}, k_{i,t}, \widetilde{\delta}_{i,t}])) \tag{8}$$

$$\widetilde{EV}_{t+1}(\widetilde{\delta}_{i,t+1}, k_{i,t+1}) =$$
$$\ln(\exp(\tilde{\delta}_{i,t+1}) + \exp(\Lambda_{0,t+1}^{k_{i,t+1}} + \vartheta_{i,j,t+1} + \beta \mathbf{E}[\widetilde{EV}_{t+2}(\widetilde{\delta}_{i,t+2}, k_{i,t+2} = k_{i,t+1}) | \tilde{\delta}_{i,t+1}, k_{i,t+1}]) \tag{9}$$

Market clear condition

- For simplicity, denote $\mathbf{E}\left[\widehat{EV}_{t+1}(\delta_{i,t},\tilde{\delta}_{i,t},k_{i,t},k_{i,t+1}=j)\right] = (\eta^{\Delta t}\mathbf{E}[EV_{t+1}(\delta_{i,t+1},k_{i,t+1}=j)|\delta_{i,t},k_{i,t}]+(1-\eta^{\Delta t})\mathbf{E}[\widetilde{EV}_{t+1}(\widetilde{\delta}_{i,t+1},k_{i,t+1}=j)|\widetilde{\delta}_{i,t},k_{i,t}])$.
- The probability of household i who owns k and purchases model j at time t is hence

$$\hat{s}^{j,k}_{i,t} = \frac{\exp\left(\Lambda_{j,t}+\vartheta_i+\varsigma_{i,j,t}+\beta\mathbf{E}\left[\widehat{EV}_{t+1}(\delta_{i,t},\tilde{\delta}_{i,t},j)\right]\right)}{\exp\left(\Lambda_{k,t}+\vartheta_i+\beta\mathbf{E}\left[\widehat{EV}_{t+1}(\delta_{i,t},\tilde{\delta}_{i,t},k)\right]\right)+\sum_{r=1}^{J}\exp\left(\Lambda_{r,t}+\vartheta_i+\varsigma_{i,r,t}+\beta\mathbf{E}\left[\widehat{EV}_{t+1}(\delta_{i,t},\tilde{\delta}_{i,t},r)\right]\right)}. \quad (10)$$

- Market equilibrium requires simulated market share equals observed market share.

$$\begin{aligned}\hat{S}_{j,t} &= \sum_{k=0}^{J}\left(\int_{D_{i,t}}\hat{s}^{j,k}_{i,t}\,dP_{D_{i,t}}\right)R_{k,t} \\ &\approx \sum_{k=0}^{J}\left(\frac{1}{N}\sum_{i=1}^{N}\hat{s}^{j,k}_{i,t}\right)R_{k,t}. \quad (11)\end{aligned}$$

  - $R_{k,t}$ is the share of households without vehicles.

Supply part

- Manufacturer f is assumed to price vehicles to maximize their profits.

$$\pi_{f,t} = \max_{\{\hat{P}_{j,t}\}, j \in \mathscr{J}_f} \sum_{j \in \mathscr{J}_f} \left(\underbrace{\frac{1-\tau_j^{ct}}{1+\tau_t^{VAT}+\tau_{j,t}}}_{\varkappa_{\tau_{j,t}}} \times \hat{P}_{j,t} - mc_{j,t} \right) \hat{S}_{j,t} M, \quad (12)$$

Datasets

- CAAM vehicle transaction data from 2007 to 2018.
  - Time, location, attributes of 165.98 million transactions.
- *autohome.com* label price data from 2012 to 2018.
  - Market prices.
- China Household Finance Survey (CHFS) in 2015.
  - We use the national income distribution to calibrate parameters.

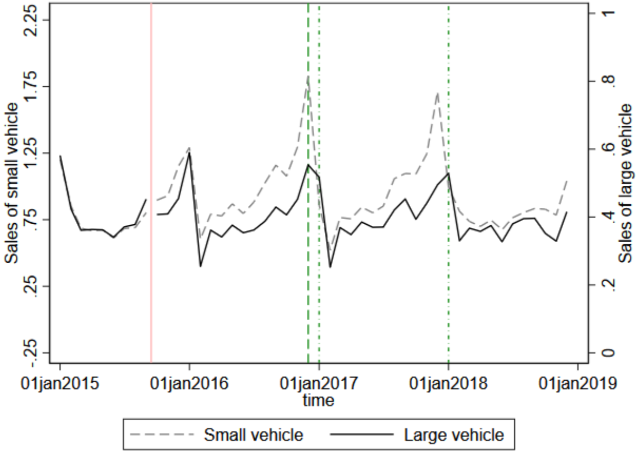


Figure 3: Sales trend of small and large vehicles

Identification of the demand model

- The demand framework encompasses a total of 17 parameters.
  - One price disutility parameter α.
  - One limited memory parameter η.
  - One time discounting parameter β.
  - Three agent specific utility dispersion factors σ^c, σ^p, π.
  - Five polynomial parameters $(\phi_1, ..., \phi_5)$ of macro utility trends $f(t)$.
  - Fixed effects λ_j associated with six car models.

- During our research window, rates of vehicle purchase tax and VAT both changed a lot, providing us rich instruments to identify the price parameter α.

$$E[\xi_{j,t}\tau_{j,t}] = 0. \tag{13}$$

$$E[\xi_{j,t}\tau_t^{VAT}] = 0. \tag{14}$$

- The identification of η relies on the fitting model predicted bunching to the real one in the data.
  - e.g. a complete myopic model ($\eta = 0$) would be rejected if sales were relocated over time,
  - and a fully rational model ($\eta = 1$) would be rejected if the sales response w.r.t. the length of preannouncement is not increasing.

$$E[\xi_{j,t} \times 1(t = k)] = 0, k \in \{t_k^I - T, ..., t_k^I, ..., t_k^I + T\}. \tag{15}$$

- We borrow $\beta = 0.9$ from Liu et al. (2020) in baseline model.

- We employ the number of competitive products at the branch level in the market, denoted as Num_t, and the count of competitive products sharing the same displacement category, denoted as $GroupNum_{j,t}$, as instrumental variables to identify σ^c and σ^p.(Berry and Haile, 2021; Gandhi and Nevo, 2021)

$$E[\xi_{j,t} Num_t] = 0. \tag{16}$$

$$E[\xi_{j,t} GroupNum_{j,t}] = 0. \tag{17}$$

- To identify π, we follow IO literature and create moments by interacting $\bar{y}_t$ with Equation (13) and Equation (14):

$$E[\xi_{j,t} \tau_{j,t} \bar{y}_t] = 0. \tag{18}$$

$$E[\xi_{j,t} \tau_t^{VAT} \bar{y}_t] = 0. \tag{19}$$

- The utility trend $f(t)$ and the vehicles' fixed effects λ_j are exogenously determined.

$$E[\xi_{j,t}t^p] = 0, p = 1, ..., 5. \tag{20}$$

$$E[\xi_{j,t}\lambda_j] = 0. \tag{21}$$

Estimation and algorithm

- We employ the Simulated Method of Moments (SMM) technique to estimate demand parameters.
  - Let Γ be the tuple of the 16 demand parameters to be estimated,
  - W be a positive definite weight matrix of various moment conditions,
  - Z be the matrix of instruments.
  - W be the weight matrix which is updated via 2-step method.

$$\hat{\Gamma} = \arg\min_{\Gamma} \xi(\Gamma)' Z W^{-1} Z' \xi(\Gamma), \tag{22}$$

- We develop a 4-layer algorithm to solve the optimization problem. (See next page)

Estimation and algorithm

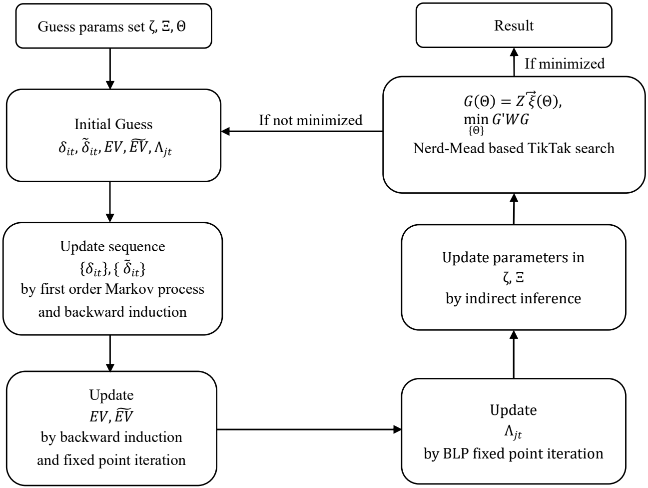


Figure 4: Estimation steps

How does limited memory influence policy effect?

- Key questions are whether there exist any optimal preannouncement length
  - maximizing sales amount so that we could promote consumption as much as possible,
  - maximizing consumer surplus and social welfare.
- Assumption we introduces in welfare analysis is $\hat{s}_{i,t}^{j,k\neq 0} = 0$.
  - This implies that tax implementation does not affect the utility of these households and hence, $\mathbf{E}[\widehat{EV}_{t+1}(\delta_{i,t}, \tilde{\delta}_{i,t}, j)]$ is identical to $\mathbf{E}[EV_{t+1}(\delta_{i,t+1}, j) | \delta_{i,t}, j]$.
  - That is, once a household makes purchase of a vehicle, he/she cannot purchase again.

Maximize sales

- Suppose tax rise policy will be implemented at t^I and is announced to the market at t^0. Hence the preannouncement length is $\Delta t = t^I - t^0$.
- Our objective is to minimize the probability that a household purchases vehicle after tax rise.
- Policy tool is preannouncement management. (i.e. choose Δt)

$$\min_{\Delta t} \prod_{\tau=t^0}^{t^I-1} \hat{s}_{i,\tau}^{0,0} \tag{23}$$

- We define $\mathcal{F}(\Delta t) := \prod_{\tau=t^0}^{t^I-1} \hat{s}_{i,\tau}^{0,0}$. Since Δt is discrete, we compare the size of $\mathcal{F}(\Delta t)$ and $\mathcal{F}(\Delta t - 1)$ to learn the monotonicity of $\mathcal{F}(\Delta t)$ in its support $[0, +\infty)$.

$$\frac{F(\Delta t)}{F(\Delta t-1)} = \underbrace{\frac{\exp\left(\mu^c_{i,0,t^0}+\mu^p_{i,0,t^0}+\beta\widehat{EV}(D_i,0,\delta_{i,t^0},\widetilde{\delta}_{i,t^0};\Delta t)\right)/\exp\left(W^d_{i,t^0}(D_i,0,\delta_{i,t^0},\widetilde{\delta}_{i,t^0};\Delta t)\right)}{\exp\left(\mu^c_{i,0,t^0}+\mu^p_{i,0,t^0}+\beta\widetilde{EV}(D_i,0,\widetilde{\delta}_{i,t^0})\right)/\exp\left(\widetilde{W}^d_{i,t^0}(D_i,0,\widetilde{\delta}_{i,t^0})\right)}}_{\text{Option value effect}}$$

$$\times \underbrace{\prod_{\tau=t^0+1}^{t^0+\Delta t-1}\frac{\exp\left(\mu^c_{i,0,\tau}+\mu^p_{i,0,\tau}+\beta\widehat{EV}(D_i,0,\delta_{i,\tau},\widetilde{\delta}_{i,\tau};\Delta t)\right)/\exp\left(W^d_{i,\tau}(D_i,0,\delta_{i,\tau},\widetilde{\delta}_{i,\tau};\Delta t)\right)}{\exp\left(\mu^c_{i,0,\tau}+\mu^p_{i,0,\tau}+\beta\widehat{EV}(D_i,0,\delta_{i,\tau},\widetilde{\delta}_{i,\tau};\Delta t-1)\right)/\exp\left(W^d_{i,\tau}(D_i,0,\delta_{i,\tau},\widetilde{\delta}_{i,\tau};\Delta t-1)\right)}}_{\text{Limited memory effect}}$$

- $\frac{F(\Delta t)}{F(\Delta t-1)}$ is decomposed into 2 parts: option value effect and limited memory effect.
  - Option value effect comes from gains of knowing tax event 1 month earlier.
  - Limited memory effect is caused by the fact that the longer is the preannouncement length, the more will be ignored by household.
- We proved that when the two parts reach a balance, i.e. $\frac{F(\Delta t)}{F(\Delta t-1)} = 1$, $F(\Delta t)$ is minimized. The minimization point is unique when $\eta \in (0,1)$.

Proposition

Optimal timing for preannouncement release to maximize sales.

(i) When $1 > \eta \geq \eta'$*, there* $\exists\ \Delta t > 0$ *that maximizes market sales;*

(ii) When $\eta' \geq \eta \geq 0$*, rolling out policy without preannouncement (i.e.* $\Delta t = 0$*) is optimal.*

The critical value of η' *is determined by equations in appendix 3.*

Maximize welfare

- Influenced by behavioral bias, households' decision utility $\mu^d_{i,j,t}$ will diverge from experienced utility $\mu^e_{i,j,t}$. We define $\Upsilon_{i,j,t} := \Lambda_{j,t} + \vartheta_i + \varsigma_{i,j,t} + \beta \mathbf{E}[EV_{t+1}(\delta_{i,t+1}, j) | \delta_{i,t}, j]$ as a shorthand expression.
  - $$\mu^d_{i,j,t} = \begin{cases} \Upsilon_{i,j,t}, j \neq 0; \\ \iota_{i,t} + \beta \mathbf{E}[\widehat{EV}_{t+1}(\delta_{i,t}, \tilde{\delta}_{i,t})], j = 0. \end{cases} \tag{24}$$
  - $$\mu^e_{i,j,t} = \begin{cases} \Upsilon_{i,j,t}, j \neq 0; \\ \iota_{i,t} + \beta \mathbf{E}[W^e_{t+1}(\delta_{i,t+1}) | \delta_{i,t}], j = 0, \end{cases} \tag{25}$$
  - $W^e_{i,t}(D_i, k, \delta_{i,t})$ is the value function of expected experienced utility.

$$\begin{aligned} & W^e_{i,t}(\Delta t) \qquad (26) \\ = \; & \Pr\left(\beta \widehat{EV}_{t+1}(\delta_{i,t}, \tilde{\delta}_{i,t}) + \varepsilon_{i,0,t} \geq \Lambda_{j,t} + \vartheta_{i,j,t} + \varepsilon_{i,j,t}, \forall j \neq 0\right) \\ & \times \left(\beta \mathbf{E}[W^e_{t+1}(\delta_{i,t+1}) | \delta_{i,t}] + \varepsilon_{i,0,t}\right) \\ & + \sum_{j=1}^{J} \Pr\left(\begin{array}{c} \Lambda_{j,t} + \vartheta_{i,j,t} + \varepsilon_{i,j,t} \geq \Lambda_{-j,t} + \vartheta_{i,-j,t} + \varepsilon_{i,-j,t}, \\ \Lambda_{j,t} + \vartheta_{i,j,t} + \varepsilon_{i,j,t} \geq \beta \widehat{EV}_{t+1}(\delta_{i,t}, \tilde{\delta}_{i,t}) + \varepsilon_{i,0,t} \end{array} \right) \end{aligned}$$

- Hence the expected utility at t^0 is

$$W_t^e = E\left\{\underbrace{W_{i,t} + \sum_{k=1}^{\Delta t-1} \beta^k W_{i,t+k} \prod_{r=0}^{k-1} s_{i,0}^{t+r}}_{\text{Option Value Gains}} \right.$$
$$\left. \underbrace{-\left(\sum_{k=1}^{\Delta t-1} \beta^k \widehat{EV}_{t+k} \prod_{r=0}^{k-1} s_{i,0}^{t+r} + \beta^{\Delta t}\left(\widehat{EV}_{t+\Delta t} - EV_{t+\Delta t}\right) \prod_{r=0}^{\Delta t-1} s_{i,0}^{t+r}\right)}_{\text{Limited Memory Loss}} \right\}$$

  - Likewise when the marginal gains and loss reach a balance, consumer surplus will be maximized. This property suggests that consumer surplus can be further improved by choosing a more appropriate preannouncement length.

Proposition

The optimal timing for preannouncement release to maximize consumer surplus is given by Δt^*, which is determined by an equation encompassing option value gains (OV) and limited memory losses (LM):

$$\Delta t = 1 + \log_\eta \frac{OV}{LM},$$

where OV and LM terms are shown in appendix 4.

Estimation results

Table 2: Model validity.

	(1) Baseline	(2) Present bias	(3) Rational decision	(4) Rational anticipation	(5) Market friction
α	-0.971***	-2.016***	-0.992***	-0.938***	-1.710***
	(0.028)	(0.030)	(0.035)	(0.037)	(0.023)
η	0.707***		1	1	
	(0.056)		-	-	
η^{PB}		0.910***			
		(0.048)			
η^{F}					0.864***
					(0.027)
σ^{p}	0.024	0.021	0.046	0.009	0.049***
	(0.045)	(0.024)	(0.046)	(0.044)	(0.006)
σ^{c}	0.033	0.007	0.013	0.009	0.033***
	(0.053)	(0.055)	(0.091)	(0.074)	(0.010)
π	0.009***	0.012***	0.015***	0.016***	0.013***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
Min of GMM	9.852	28.077	10.534	11.920	20.487

- We measured the performance of different models by the global minimization value of the objective function following Ganong et al. (2019 AER).
- Overall, our baseline model fits best.

Present bias

To empirically examine the suitability of present bias for the data, we introduced the present bias parameter η^{PB} into our model. We postulate that this parameter, η^{PB}, influences the indirect utility of household i's outside option, which is shown as follows:

$$V_{i,0,t}^{PB} = \eta^{PB}\beta E[EV_{i,t}(\delta_{i,t+1})|\delta_{i,t}] + \varepsilon_{i,0,t}. \tag{27}$$

Market friction

In this context, the cumulative distribution function for $\varepsilon_{i,j,t}$ is represented as:

$$F(\varepsilon_{i,j,t}) = e^{-e^{-\frac{\varepsilon_{i,j,t}}{\eta^F}}}. \tag{28}$$

The associated probability to purchase model j of household i is

$$s_{i,t}^{j,k} = \frac{\exp(\frac{\Lambda_{j,t}+\vartheta_{i,j,t}}{\eta^F})}{\sum_{r=1}^{J}\exp(\frac{\Lambda_{r,t}+\vartheta_{i,r,t}}{\eta^F}) + \exp(\frac{\beta\widehat{EV}_{t+1}(\delta_{i,t},\tilde{\delta}_{i,t})}{\eta^F})}. \tag{29}$$

Table 3: Model extensions

	(1) Baseline	(2) Dynamic pricing	(3) Memory decay
α	-0.971***	-2.116***	-0.992***
	(0.028)	(0.063)	(0.024)
η	0.707***	0.056	0.783***
	(0.056)	(0.041)	(0.049)
σ^p	0.024	0.059***	0.020
	(0.045)	(0.012)	(0.045)
σ^c	0.033	0.006	0.023
	(0.053)	(0.007)	(0.062)
π	0.009***	0.003	0.005**
	(0.002)	(0.003)	(0.002)
Min of GMM	9.852	23.761	13.207

Dynamic pricing

- Specifically, we adopt the dynamic revenue management framework proposed by Williams (2022), where a manufacturer f's objective is to set a sequence of prices $\{P_{j,t}\}$ maximizing the expected present discounted value of profits from all the products, $E_\tau \sum_{\tau=t}^{\infty} \beta^{\tau-t} \pi_{f,t}$.

$$\begin{aligned} V(R_t, mc_{j,t}, \delta_{i,t}, \tilde{\delta}_{i,t}) &= \max_{P_{j,t}} \Big[\pi_{f,t} + \beta \int V(R_{t+1}, mc_{j,t+1}, \delta_{i,t+1}, \tilde{\delta}_{i,t+1}) \\ &\times \quad dF(mc_{j,t+1}, \delta_{i,t+1}, \tilde{\delta}_{i,t+1} | mc_{j,t}, \delta_{i,t}, \tilde{\delta}_{i,t}) \Big], \\ s.t. R_{t+1} &= R_t \left(1 - \sum_{f=1}^{6} \hat{S}_{j,t} \right) + N_{t+1}. \end{aligned} \tag{30}$$

$$\hat{S}_{j,t} + (P_{j,t} - mc_{j,t}) \frac{\partial \hat{S}_{j,t}}{\partial \hat{P}_{j,t}} \frac{\partial \hat{P}_{j,t}}{\partial P_{j,t}} - \beta \left(P_{j,t+1} - mc_{j,t+1} \right) \hat{S}_{j,t+1} \sum_{k=1}^{J} \frac{\partial \hat{S}_{k,t}}{\partial \hat{P}_{j,t}} \frac{\partial \hat{P}_{j,t}}{\partial P_{j,t}} = 0. \tag{31}$$

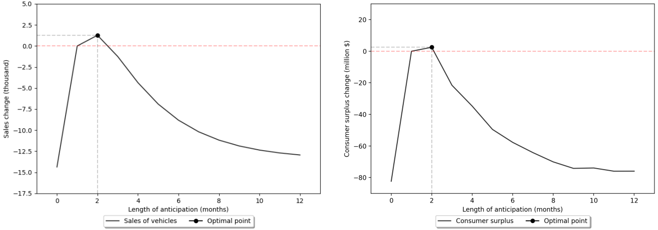
Memory decay

- Memory deteriorates over time.

$$\begin{aligned} \mathbf{E}\left[\widehat{EV}_{t+1}\left(\delta_{i,t},\tilde{\delta}_{i,t},j\right)\right] &= \eta^{t-t^A}\mathbf{E}\left[EV_{t+1}(\delta_{i,t+1},j)|\delta_{i,t},j\right] \\ &+ \left(1-\eta^{t-t^A}\right)\mathbf{E}\left[\widetilde{EV}_{t+1}(\tilde{\delta}_{i,t+1},j)|\tilde{\delta}_{i,t},j\right]. \end{aligned} \tag{32}$$

Optimal preannouncement design

- We find that the best timing to release tax rise preannouncement is 2 months in advance, suppose the objective is to maximize social welfare or vehicle sales.

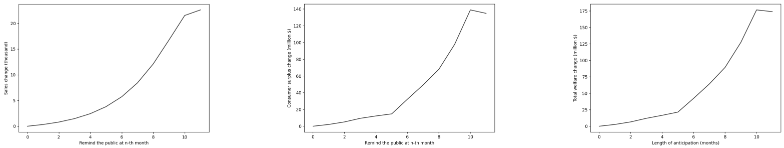


(a) Sales (b) Consumer surplus

Figure 5: Welfare implication.

Remedy by sending reminders

- One alternative way to improve policy efficacy is to remind the public of coming policy deadlines.

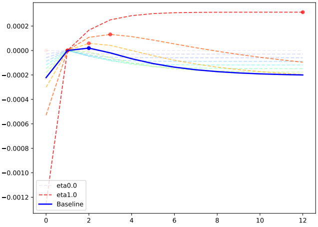


(a) Sales (b) Consumer surplus (c) Social welfare

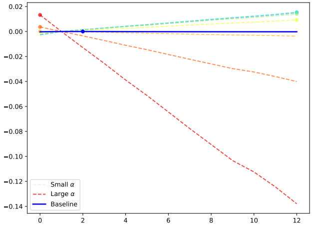
Figure 6: Remedy design with fixed memory weight

Comparative statics

- How do attention, demand elasticity, income distribution, and inflation projection matter for preannouncement management?



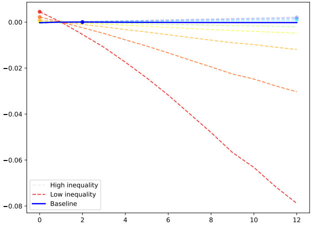
(a) Attention



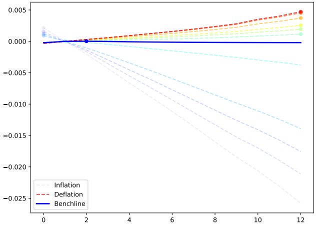
(b) Demand elasticity

Figure 7: Optimal timing across diverse parameters.

Comparative statics



(a) Income heterogeneity



(b) Inflation

Figure 8: Optimal timing across diverse parameters.

Conclusion

- By studying the tax rate notches over time, our research records evidence of strong decision friction in the market. Such friction increases with preannouncement length.
- We use limited memory theory to explain the evidence and embed it into a dynamic discrete choice model.
- Our theoretical framework shows that the extent of limited memory and option value effects together determine the optimal length of preannouncement, which minimizes the probability of missing a deadline.

- Counterfactual simulation suggests that the optimal preannouncement length that maximizes consumer surplus is 2 months ahead of policy implementation.
- Our estimation aggregates data to segment level, breaking the original market competition among firms. In future work, we will endeavor to further simplify the algorithm. We are also committed to developing additional new policy tools for fiscal analysis.

Thanks!

Vehicle sales and attributes

- Monthly vehicle model level sales from the China Association of Automobile Manufacturers (CAAM) from 2007 to 2018.
  - The data documents over 165.98 million transactions.
  - It records the location of transaction as well.
  - It covers vehicle characteristics including cylinder capacity (L), fuel cost (L/100km), weight (kg), vehicle type (sedan, SUV, or MPV), etc.

Transaction label price

- *autohome.com* has over 2.2 million comments from different buyers during 2012-2018. All comments contain the model of vehicles, reported label prices, purchase locations, and purchase time. We scraped the data and then merge it into our sales data.
- Relation between label prices $P_{c,j,t}$ and total prices $\hat{P}_{c,j,t}$

$$\hat{P}_{c,j,t} = P_{c,j,t} \times \left(1 + \frac{\tau_{j,t}}{1 + \tau^{VAT}}\right) \tag{33}$$

- $\hat{P}_{c,j,t}$ is the total price, $P_{c,j,t}$ is the label price, τ_t^{VAT} means VAT tax rate, $\tau_{j,t}$ is the rate of vehicle purchase tax.

Market demographic data

- Households demographic characteristics data is from China Household Finance Survey (CHFS) in 2015.
- The survey covers 37289 households and is carefully designed so that it can reflect households' income and financial status very well.
- We use the national income distribution to calibrate parameters.

Proposition

Optimal timing for preannouncement release to maximize sales.

(i) When $1 \geq \eta \geq \max\{\eta', \eta''\}$, there $\exists\, \Delta t > 0$ that maximizes market sales;

(ii) When $\eta'' \geq \eta \geq 0$, rolling out policy without preannouncement (i.e. $\Delta t = 0$) is optimal.

The critical value of η' is determined by equation

$$\eta = \frac{m_{T_U+1}\left(1 - s_{i,0}^{T_U}(1)\right)}{\left(1 - s_{i,0}^{T_U}(2)\right) + m_{T_U}\left(1 - s_{i,0}^{T_U-1}(2)\right)},$$

and η'' is determined by equation

$$\frac{\left(E\left[\widetilde{EV}_{i,T_U+1}\right] - E\left[EV_{i,T_U+1}\right]\right) \times \left(1 - s_{i,0}^{T_U}(1)\right)}{2\left(1 - s_{i,0}^{T_U}(2)\right)\left(E\left[\widetilde{EV}_{i,T_U+1}\right] - E\left[EV_{i,T_U+1}\right]\right) + 2\left(1 - s_{i,0}^{T_U-1}(2)\right)\left(E\left[\widetilde{EV}_{i,T_U}\right] - E\left[EV_{i,T_U}\right]\right)} = 0.$$

Proposition

The optimal timing for preannouncement release to maximize consumer surplus is given by Δt^*, which is determined by an equation encompassing option value gains (OV) and limited memory losses (LM):

$$\Delta t = 1 + \log_{\eta} \frac{OV}{LM},$$

where OV and LM terms are

$$\begin{aligned}
OV \quad = \quad & \ln \left(\frac{\exp\left(\delta_{i,t}\right) + \exp\left(\beta \widehat{EV}_{i,T_L+1}\right)}{\exp\left(\delta_{i,t}\right) + \exp\left(\beta \widetilde{EV}_{i,T_L+1}\right)} \right) \\
& - \sum_{k=1}^{\Delta t-1} \beta^k \left(\widetilde{EV}_{i,T_L+k} - W_{i,T_L+k} \right) \left(\prod_{r=0}^{k-1} s_{i,0}^{T_L+r} - s_{i,0}^{T_L,na} \prod_{r=1}^{k-1} s_{i,0}^{T_L+r,\Delta t-1} \right) \\
& - \beta^{\Delta t} \left(\widetilde{EV}_{T_L+\Delta t} - EV_{T_L+\Delta t} \right) \left(\prod_{r=0}^{\Delta t-1} s_{i,0}^{T_L+r} - s_{i,0}^{T_L,na} \prod_{r=1}^{\Delta t-1} s_{i,0}^{T_L+r,\Delta t-1} \right)
\end{aligned}$$

$$
\begin{aligned}
LM \quad = \quad & \left(\sum_{k=2}^{\Delta t-1} \beta^k \left(EV_{i,T_L+k} - \widetilde{EV}_{i,T_L+k} \right) \left(\eta \prod_{r=0}^{k-1} s_{i,0}^{T_L+r} - s_{i,0}^{T_L,na} \prod_{r=1}^{k-1} s_{i,0}^{T_L+r,\Delta t-1} \right) \right. \\
& \left. + \beta\eta \left(EV_{i,T_L+1} - \widetilde{EV}_{i,T_L+1} \right) s_{i,0}^{T_L} \right)
\end{aligned}
$$