Electricity Tariff Rate Design and Optimization

Existing Research

The Efficiency of Dynamic Electricity Prices

01. **Question**
Can feasible TOU and CPP prices substantially improve alignment between cost and price?

02. **Paper's solution**
Using combination of TOU rates and limited number of yearly CPP days with rates set based on day-ahead prices

02. **Paper's model performance metric**
Renormalized R-squared error value: percentage of deadweight loss recovered by using proposed policies compared to a flat tariff with the same information

03. **Research extension directions**
Further research on ideal granularity of pricing tiers and timeliness of rates.
More exploration on distributional impacts of alternative rate designs on different groups of people (income, region, usage patterns) besides just overall efficiency of the system.
In depth analysis on how to accommodate for changing behavioral responses (load shifting) as a result of proposed rate structures.

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Prior Literature

The Efficiency of Dynamic Electricity Prices

1. Theoretical Foundations of Real-Time Pricing

- **Boiteux (1949)**: Early economic theory advocating for pricing that reflects marginal cost and scarcity.
- **Joskow (1976)**: Emphasized economic efficiency through real-time pricing mechanisms.
- **Borenstein and Holland (2005)**: Argued that real-time pricing aligns prices with the true cost of electricity, improving efficiency and reducing overuse during peak times.

2. Modeling and Estimation Tradeoffs

- **James, Witten, Hastie, and Tibshirani (2021)**: Showed that while complex functional forms can capture variation, they risk overfitting and performing poorly on out-of-sample data.
- **Chu, Leslie, and Sorensen (2011)**: Demonstrated that simple subsets of complex pricing schemes can be nearly optimal for firms selling multiple retail products.

Prior Literature

The Efficiency of Dynamic Electricity Prices

3. Empirical Evaluation of Time-Varying Pricing Schemes

A. Time-of-Use (TOU) Pricing

- **Aigner (1984)**: One of the earliest empirical evaluations of TOU electricity pricing.
- **Train and Mehrez (1994)**: Assessed consumer behavior under TOU pricing.
- **Enrich, Li, Mizrahi, and Reguant (2024)**: Recent analysis of TOU pricing, focusing on behavioral and efficiency outcomes.

B. Critical-Peak Pricing (CPP)

- **Wolak (2007, 2011a)**: Analyzed consumer responses and welfare gains from critical-peak pricing.
- **Ito, Ida, and Tanaka (2018)**: Experimental evidence on demand response to CPP in Japan.
- **Blonz (2022)**: Examined the effectiveness and equity implications of CPP programs.

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Prior Literature

The Efficiency of Dynamic Electricity Prices

3 cont. Empirical Evaluation of Time-Varying Pricing Schemes

C. Real-Time Pricing (RTP) Pilots

- **Allcott (2011)**: Field experiment on real-time pricing and its effect on household electricity use.
- **Andersen, Hansen, Jensen, and Wolak (2017)**: Studied household responsiveness to dynamic prices in Denmark.
- **Fabra, Rapson, Reguant, and Wang (2021)**: Evaluated RTP adoption and outcomes using randomized pricing experiments.

4. Market Simulations of Pricing Schemes

- **Borenstein (2005a, 2005b)**: Used simulations to compare flat rates, TOU, and RTP pricing in electricity markets.
- **Borenstein and Holland (2005)**: Modeled the welfare and emissions implications of alternative electricity pricing.
- **Holland and Mansur (2006)**: Assessed market and environmental outcomes of pricing policies using simulation-based approaches.

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Research Gap and Questions

The Efficiency of Dynamic Electricity Prices

Retail vs. Marginal Cost Misalignment
Time-invariant rates ignore real-time cost fluctuations → efficiency loss.

Limited Responsiveness in Current TOU/CPP
Tariffs (e.g., SDG&E) are fixed in advance → no response to real market conditions.

Coarse Temporal & Spatial Granularity
On/off-peak rates miss variation *within peaks*, *across days*, and *across locations*.

Balancing Simplicity vs. Accuracy
Complex pricing may better match costs but is often deemed too confusing for households.

Key Questions

- How well do TOU/CPP rates approximate wholesale price variation?
- Is **granularity** or **timeliness** more critical? (Borenstein 2005b)
- What's the efficiency gain with growing AMI and new load (e.g., data centers)?

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Methods

The Efficiency of Dynamic Electricity Prices

1. **Machine Learning Exercise**
   - Used to evaluate how different pricing structures perform.
   - Shows that **most efficiency gains come from a simple two-tier TOU plan**.
2. **Wholesale Market Data Analysis**
   - Based on **2 decades of hourly marginal cost data** from **all 7 U.S. wholesale electricity markets**.
   - Focuses on **equilibrium prices** to account for:
     - **Out-of-sample fit**
     - **Equilibrium price effects** of alternative pricing schemes.
3. **Regression Model**
   - **Dependent variable**: Hourly wholesale electricity price yi.
   - **Explanatory variables**: Dummy indicators Dk representing specific hours or pricing tiers.
   - **Focus**: Not on the estimated price levels (β), but on **goodness-of-fit statistics**.

$$y_{is} = \sum_k \beta_k D_{is}^k + \varepsilon_{is},$$

4. **Simulated Equilibria**
   - Simulates retail pricing policies and their resulting **equilibrium wholesale prices**.
   - Benchmarks welfare using **deadweight loss (DWL)** comparisons.

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Metrics

The Efficiency of Dynamic Electricity Prices

$$R^2 = 1 - \sum_i (y_i - \hat{y}_i)^2 / \sum_i (y_i - \bar{y})^2$$

$$\text{Renormalized } R^2 = \frac{R_P^2 - R_B^2}{1 - R_B^2},$$

1. **OLS R^2 (In-Sample Goodness of Fit)**
   - Measures how well retail prices (based on a policy) explain historical wholesale prices.
   - **Upper bound** on potential efficiency gains.
2. **Out-of-Sample R^2**
   - Applies coefficients from one sample to a different set of data.
   - Represents how well a policy trained on past data would perform in the future. **Biased** due to unrealistic reliance on known future outcomes.
3. **Renormalized R^2 (Preferred Metric)**
   - Captures the **percentage of deadweight loss (DWL) recovered** by a pricing policy relative to the best possible flat tariff. Benchmarked using **forecast-informed flat pricing** as the baseline.
   - Values range from:
     - **0**: Equivalent to best flat rate using same info
     - **1**: Full real-time pricing (theoretical maximum, but problematic due to equilibrium feedback effects)

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Findings Summary

The Efficiency of Dynamic Electricity Prices

Overall Efficiency Gains from Pricing Policies

1. **Mispricing inefficiencies estimated at ~$2 billion annually**.

2. **Two-tiered TOU plans** capture **most of the efficiency gains** with minimal complexity.
   - **Best subset selection algorithms** are used to find globally optimal pricing policies (e.g., how many levels, time splits).
3.
4. **TOU and CPP policies each capture ~10% efficiency gains**; **combined policies provide mostly additive gains**.

5. **Getting the average price level right** is more impactful than matching hourly variation in prices.

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Findings Summary

The Efficiency of Dynamic Electricity Prices

Design and Evaluation of TOU Plans

6. **Timeliness of pricing** matters more than fine-grained TOU rate schedules.
7. **Granular TOU plans** may **worsen performance** due to **overfitting** and **pricing errors** (e.g., misidentifying peak vs. off-peak).
8. **Out-of-sample performance** declines for highly granular pricing schemes due to sparse training data.
9. **Day-ahead calling/pricing** improves efficiency significantly, even if not as optimal as real-time.

Design and Evaluation of CPP

10. **Uniform CPP prices across events** limit efficiency, even with more events per year.
11. **Differentiating prices for very high-cost days** yields gains if demand response is elastic.
12. CPP policy performance improves with **locational granularity**, more so than TOU.

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Findings Summary

The Efficiency of Dynamic Electricity Prices

Modeling and Policy Selection

13. **Policies trained on historical data** often perform worse out-of-sample than simpler designs.

14. **Simple TOU or CPP policies** can **match or outperform** more complex ones when evaluated on unseen data.

Market-Specific Considerations

16. **Pricing policy performance varies by market** — some benefit more from time-varying rates than others.

17. **Efficiency gains are calculated using renormalized R^2 differences**, interpreting differences in deadweight loss (DWL).

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Future Work Direction

The Efficiency of Dynamic Electricity Prices

1. **Fixed Cost Recovery & Non-Marginal Components**
 Study how rate structures can also account for fixed infrastructure costs, customer service, and non-marginal price components included in retail bills.

2.

3. **Incorporating Environmental Externalities**
 Extend analysis to include emissions pricing or carbon externalities, which affect the social marginal cost and can shift the efficient price level.

4. **Integration with Emissions-Based Rate Reforms**
 Explore how real-time pricing can be paired with policies targeting environmental goals (e.g., carbon pricing or clean energy incentives)

5.

6. **Distributional Effects on Customer Segments**
 Analyze the **equity impacts** of TOU and CPP pricing across income levels, household types, or load profiles (e.g., seniors, renters, EV users).

7. **Granular Load Analysis with Better Data**
 Move beyond ISO-level aggregate hourly data to study customer behavior and pricing impacts using **nodal or substation-level load data**, where available.

8. **Demand Response in Locational Pricing Models**
 Evaluating how retail customers respond to spatially varying price signals.

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Research Goal

Develop an electricity tariff rate structure that integrates existing rate designs, consumer load profiles, nonlinear demand-responsive pricing, and temporal and seasonal consumption trends across California's distinct climate zones.

Utility profits

Minimize deviations in utility profit (revenue)

Load profiles

Minimize deviation/impact on consumer behavior **(load shifting effects)**

Existing Structures

Analyze whether proposed rates capture market trends and improves on existing rates

Research gap

Unlike current research that typically considers only a few components of electricity cost—such as demand, transmission, and grid maintenance—our study incorporates eight distinct components from the E3 ACC dataset, enabling a more granular and accurate analysis of pricing structures.

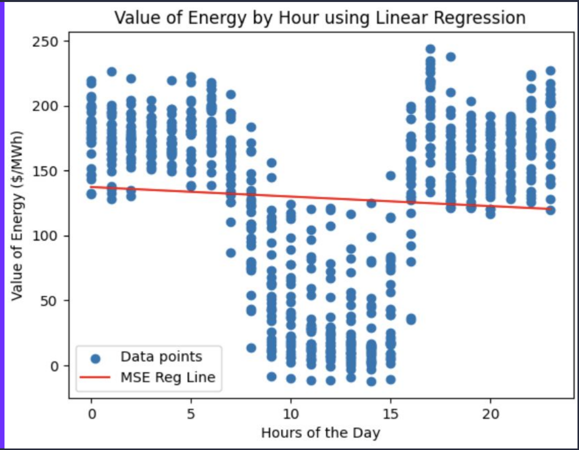
In addition, this research will extend existing analysis from The Efficiency of Dynamic Electricity Prices paper (see prev slide)

Rate comparisons

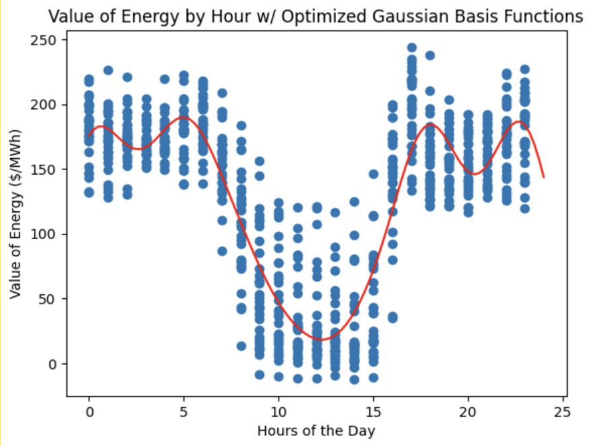
Existing utility TOU rates v. previously proposed rate models

Proposed rate models so far

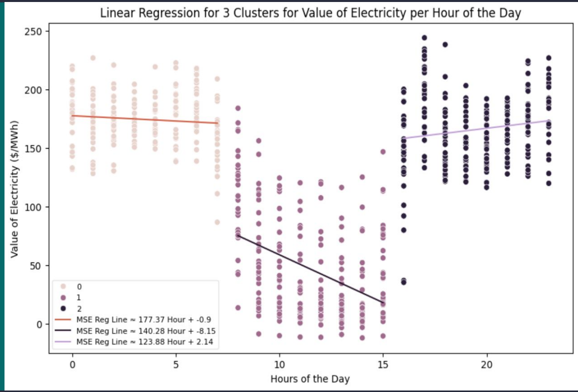
Linear



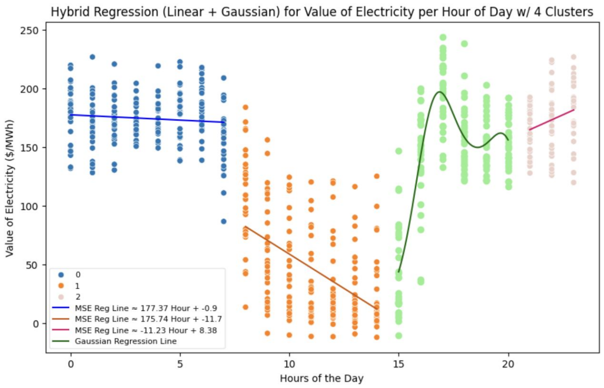
Gaussian



Cluster + Linear

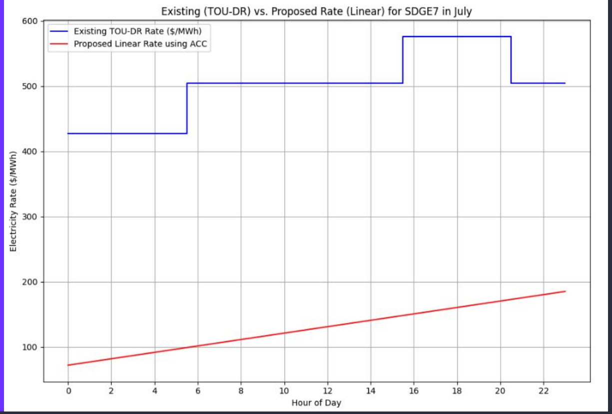


Cluster + Linear + Gausian

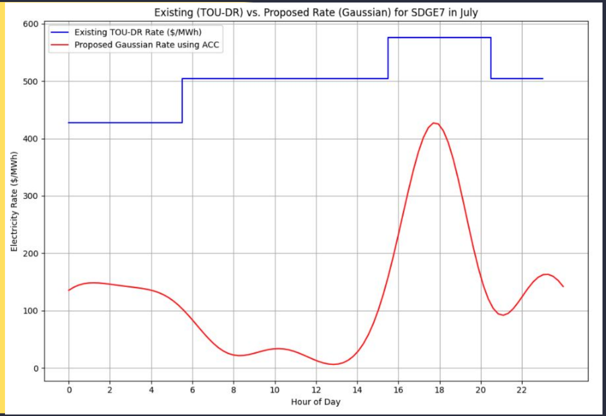


Comparing Rates: Existing v. Proposed Models

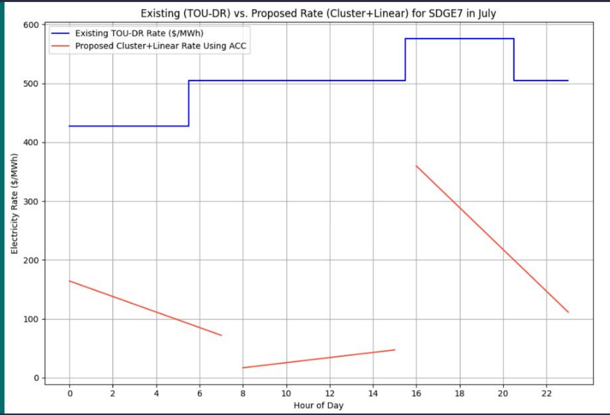
Linear



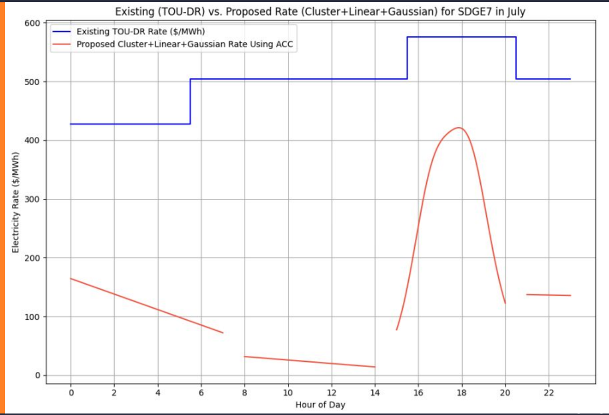
Gaussian



Cluster + Linear



Cluster + Linear + Gausian



Formulating the objective functions

Mathematically modeling the proposed models using empirical risk minimization wrt. MSE

Linear and Gaussian models

Model | **Objective function**

Linear

$$\min_{\vec{w}} \frac{1}{n} \|X\vec{w} - y\|_2^2$$

- n = # of climate zones
- T = number of hours
- λ is the weight placed on the regularization term
- $y \in \mathbb{R}^{n \times T}$ is the true hourly rates from E3 ACC
- $X \in \mathbb{R}^{n \times T \times (d+1)}$
- $\vec{w} \in \mathbb{R}^{d+1}$ is the weights vector

Gaussian

$$\min_{\vec{w},\vec{\mu},\vec{\sigma}} \frac{1}{n} \sum_{i=1}^{n} \left(\vec{w}^{\top}\phi(X_i;\vec{\mu},\vec{\sigma}) - \vec{y}_i\right)^2$$

$$\phi(X_i;\vec{\mu},\vec{\sigma}) \in \mathbb{R}^{T \times k} := \exp\left(-\frac{(x-\mu_i)^2}{\sigma_i^2}\right)$$

which is a design matrix with feature maps

- k = number of Gaussian basis functions
  - $X_i \in \mathbb{R}^{T \times (d+1)}$ is the input features matrix
  - μ_i is the center of each bump
  - σ_i is the width of each bump
- $\vec{w} \in \mathbb{R}^k$ is the weights for each basis function
- $\vec{y}_i \in \mathbb{R}^T$ the true rates according to E3 ACC

Clustering piecewise models

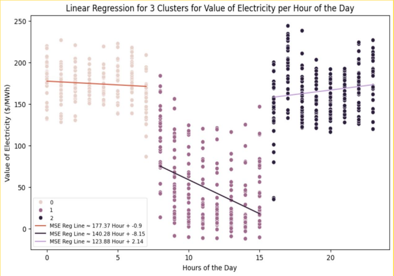
Model

Objective function

Cluster
+ Linear

$$\min_{\{\vec{w}^{(j)}\}_{j=1}^{3}} \quad \frac{1}{n}\sum_{i=1}^{n}\sum_{t=1}^{24}\left(\sum_{j=1}^{3} \mathbb{1}_j(t)\cdot\left(X_{it}^{\top}\vec{w}^{(j)} - y_{it}\right)\right)^2$$

- $\vec{w}^{(j)} \in \mathbb{R}^{d+1}$ is the weigh vector for cluster j
- $X_{it} \in \mathbb{R}^{d+1}$ is the feature vector for climate zone i at hour t
- $\mathbb{1}_j(t) \in [0,1]$ is an indicator function: 1 if t in cluster j, else 0



Cluster
+ Linear
+ Gaussian

$$\min_{\substack{\vec{w}^{(1),(2),(4)}\in\mathbb{R}^{d+1},\\ \vec{w}^{(3)}\in\mathbb{R}^{K}}} \left\{\frac{1}{n}\sum_{i=1}^{n}\sum_{t=1}^{24}\left[\sum_{j=1}^{4}\mathbb{1}_j(t)\cdot\left(f^{(j)}(X_{it}) - y_{it}\right)\right]^2\right\}$$

$$f^{(j)}(X_{it}) = \begin{cases} X_{it}^{\top}\vec{w}^{(j)} & \text{if } j \in \{1,2,4\} \\ \phi(X_{it};\vec{\mu},\vec{\sigma})^{\top}\vec{w}^{(3)} & \text{if } j = 3 \end{cases}$$

← Linear segments
← Nonlinear segments

Rate-policy informed modeling:
Adding a penalty parameter

Leveraging electricity pricing domain trends to design a hybrid statistical tariff model that minimizes error from the average market value of electricity, while incorporating policy- and economics-driven regularization.

$$\text{minimize } MSE(\hat{y}, y) + \lambda\underbrace{(\Pi_{\text{proposed model}} - \Pi_{\text{existing model}})}_{\text{Penalty/regularization parameter}}$$

Linear and Gaussian models

Model | **After utility profit regularization**

Linear

$$\min_{\vec{w}} \frac{1}{n}\|X\vec{w} - y\|_2^2 + \lambda \sum_{i=1}^{n}((X_i\vec{w} - \vec{r}_i^{\text{ existing}})^\intercal \vec{d}_i)$$

- $X_i \in \mathbb{R}^{T\times(d+1)}$ is the input features matrix for climate zone i
- $X_i\vec{w} = \hat{y} \in \mathbb{R}^T$ is the predicted electricity rate ($/MWh) for each hour
- $\vec{r}_i \in \mathbb{R}^T$ is the existing rate structure for climate zone i
- $\vec{d}_i \in \mathbb{R}^T$ is climate zone i's load demand (aggregated from all the buses in climate zone)

Gaussian

$$\min_{\vec{w},\vec{\mu},\vec{\sigma}} \frac{1}{n}\sum_{i=1}^{n}\left(\vec{w}^\intercal\phi(X_i;\vec{\mu},\vec{\sigma}) - \vec{y}_i\right)^2 + \lambda\sum_{i=1}^{n}((\vec{w}^\intercal\phi(X_i;\vec{\mu},\vec{\sigma}) - \vec{r}_i^{\text{ existing}})^\intercal\vec{d}_i)$$

- $(\vec{w}^\intercal\phi(X_i;\vec{\mu},\vec{\sigma}) - r_i^{\text{existing}}) \in \mathbb{R}^T$ controls the strength of the regularization to avoid overfitting

Clustering piecewise models

Model

After utility profit regularization

Cluster + Linear

$$\min_{\{\vec{w}^{(j)}\}_{j=1}^{3}} \quad \frac{1}{n}\sum_{i=1}^{n}\sum_{t=1}^{24}\left(\sum_{j=1}^{3} \mathbb{1}_j(t)\cdot(X_{it}^\top \vec{w}^{(j)} - y_{it})\right)^2 + \lambda \sum_{i=1}^{n}\sum_{t=1}^{24}\left(\sum_{j=1}^{3} \mathbb{1}_j(t)\cdot(X_{it}^\top \vec{w}^{(j)} - r_{it}^{\text{existing}})\right)\cdot d_{it}$$

Cluster + Linear + Gaussian

$$\min_{\substack{\vec{w}^{(1),(2),(4)}\in\mathbb{R}^{d+1},\\ \vec{w}^{(3)}\in\mathbb{R}^{K}}} \left\{\frac{1}{n}\sum_{i=1}^{n}\sum_{t=1}^{24}\left[\sum_{j=1}^{4} \mathbb{1}_j(t)\cdot\left(f^{(j)}(X_{it}) - y_{it}\right)\right]^2 + \lambda\sum_{i=1}^{n}\sum_{t=1}^{24}\left[\sum_{j=1}^{4} \mathbb{1}_j(t)\cdot\left(f^{(j)}(X_{it}) - r_{it}^{\text{existing}}\right)\cdot d_{it}\right]\right\}$$

$$f^{(j)}(X_{it}) = \begin{cases} X_{it}^\top \vec{w}^{(j)} & \text{if } j\in\{1,2,4\} \\ \phi(X_{it};\vec{\mu},\vec{\sigma})^\top \vec{w}^{(3)} & \text{if } j = 3 \end{cases}$$

Next steps

01. **Incorporate additional regularization terms to reflect consumer load demand**

02. **Aggregate and analyze data across three distinct seasonal periods**

03. **Separate and evaluate fixed vs. marginal cost data**

04. **Begin drafting the research paper and outlining methodology**

Thank you