# Discussion of “Decoding China’s Industrial Policies” by Fang, Li, and Lu

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# Before them

- Measuring global industrial policies from text (Juhaz et al., 2022)
    - Identifying industrial policies from Global Trade Alert (GTA) policy summaries from 2010 to 2022
    - Key insight: extend our attention from subsidies and tarrifs to policy tools that can't be easily put into numbers, such as administrative guidance
        - Doing this at scale requires machine learning, NLP in particular
    - Policy categories taken directly from GTA database, covering diverse policy instruments commonly seen across all countries → many are trade-related measures
- Mixed results on effectiveness and consequences of a (suite of) major policies in a given industry (Barwick et al., 2023, 2024; Lane, 2024)
- The political economy of policy implementation (Xu, 2011; Wang & Yang, 2024)

# Fang, Li, and Lu

- Present paper wants to have a comprehensive view of industrial policies in China, at various levels of the government, across different sectors
- Offer new data and LLM-based approach that provides
  - a set of all **industrial policy documents** and associated policy instruments, citations across the bureaucracy, and details about policy implementation
  - **quantitative evidence** on policy diffusion, policy passthrough, local policy experimentation, effectiveness of policy tools
  - **insight** on the political economy of China's IPs
- Goal is ambitious and using LLMs to do complex information extraction at scale will require careful design and validation

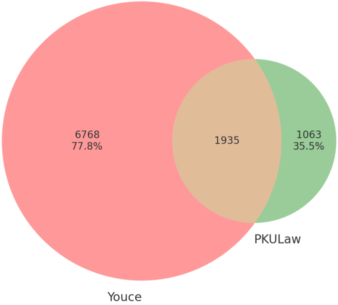
# Data

- Data source for policy documents: PKULaw.com + continuous webscraping
  - PKULaw coverage for central government is comprehensive for all types of documents
  - But maybe not for local government policies
  - Webscraping local governments' websites is not a trivial task
- Is this the universe of industrial policies, or at least a representative sample of them?

| Platform | Data Volume (Deduped) | Policy Level Coverage | Tech Stack | Data Maintenance |
|---|---|---|---|---|
| Youce (优策) | 16.65–17.575 million (incl. 9.52M news) | Central + local coverage | In-house algorithms + general LLM | Continuous |
| PKULaw (北大法宝) | 4.51 million | Stronger central policy coverage | Manual tagging | Continuous |
| ChaCe (查策网) | 0.89 million (not deduped) | More complete local coverage; skewed toward firm-support policies | Manual tagging | Some data outdated or inactive |

# Data: a toy example with the EV sector

- Start with a search for all policy documents that contain EV-sector keywords in the title, such as “new energy vehicle, ” ”electric vehicle,” ”new energy bus,”, “hybrid vehicle”
- Then identify a match using fuzzy matching plus LLM (GLM4)
- So how does the coverage compare?



# Example policy tool classification


```json
{
    "cleaned_data": "\n关于征集泰安市2024年电动车以旧换新活动回收企业的通知.pdf\n",
    "title": "关于征集泰安市 2024 年电动自行车以旧换新活动回收企业的通知",
    "id": "6714aa05da863c1320b7e3e6"
},
```


Input sample


```json
{
    "id": "6714aa05da863c1320b7e3e6",
    "title": "关于征集泰安市 2024 年电动自行车以旧换新活动回收企业的通知",
    "cleaned_data": "\n关于征集泰安市2024年电动车以旧换新活动回收企业的通知.pdf\n",
    "predict_": {
        "type": [
            "Definitely Not EV IP"
        ]
    }
}
```


Model output

# Prompt example

```
title = sample_in_prompt["title"]
cleaned_content = sample_in_prompt["cleaned_content"]
output = f'```json {json.dumps({"type": [_item for item in sample_in_prompt["taxonomy"] for _item in item]})}```'

instruction = """
###指令###
你是一个专业的政策分类工具，你的任务是根据给定的政策标题和内容，判断其属于以下哪些类别：
- Definitely Not EV IP: 不属于新能源汽车行业的产业政策。其中包括非产业政策，以及非新能源汽车行业的产业政策。仅仅作为管理者、服务者的政府颁布的政策不被视为产业政策，例如公
- Guidance: 方针指导性质的文件。包括各级政府部门对新能源汽车、新能源汽车电池、新能源基础设施等的方针指导。
- Subsidies: 补贴。包括各类补助资金、补贴奖励、更新补助、差价补贴等。注意修改或发布《新能源汽车推广应用推荐车型目录》的政策也是此类，因为列入这一《目录》的新能源车将受到新
- Tax: 税收优惠。包括车船税、购置税等。调整享受税收优惠的新能源车技术标准的政策也是此类。
- Elimination: 落后产能的退出。
- Policy Loans: 给予政策性贷款。
- Procurement: 政府采购。
- Talent: 人才支持政策。
- Gov Guidance Funds: 政府发展基金支持。
- Technical Standard: 新能源车整车或零部件的技术标准。
- Environmental Protection: 环保相关的政策。例如与新能源汽车蓄电池回收相关的政策等。

###输出格式###
以JSON格式输出一个或多个类别。例如：
```json {type: [Guidance, Elimination]}```
""" + f"""
###范例###
政策标题：{title}
政策内容：{cleaned_content}
输出：{output}
"""
```
```

# LLM approach

Prompting strategy: formalised checklist of subquestions forces the model to reason transparently and avoid hallucinated leaps of logic.

- Intuition: hallucinated claims rarely survive the verbatim-evidence check

Additional refinement for high-stake tasks

- high-stake tasks: determining IP, policy tool classification, target industry
- low-stake tasks: policy objectives, conditionality, policy citation (motives and hierarchy), etc

# LLM approach

One key is to **control the output** of LLMs – fundamentally a “prompt tuning” approach.

- model choice: multilingual, long context window to accomodate detailed prompts
- single-agent extractor plus a reviewer running in series
- effective adaption of common techniques: focusing on relevant text for QA, think step by step, majority voting

How do we evaluate the performance of the model to say that this “works well” and is robust to hallucination?

Are potential measurement error from querying blackbox LLMs better/worse than potential measurement error from training ML algorithms with hand-labeled data?

# Policy classification: Our ongoing work on the NEV sector

- **Data:** 15,337 policy documents from 2003 to Oct 2024 from Youce
- **Task:** classify policy documents into 11 policy categories (including one for non-IP), following Branstetter and Li (2024) and allowing for multi-labels
  - Within the subsidy category, further divide into 6 types
- Our approach: fine-tuning small open-source LLMs using hand-labeled data
  - Random stratified sampling of policy docs for train (70%) / test (30%)
  - To address class imbalances, employ data augmentation technique
  - Prompt design: tested both longer, more detailed and shorter category descriptions; manual adjustment based on mistakes
  - Final policy label prediction is the ensemble of three top performing models

# Policy instruments

| General Policy Categories (10 categories + Not IP) |
|---|
| Definitely Not EV IP |
| Guidance |
| Subsidies |
| Tax |
| Procurement |
| Technical Standard |
| Environmental Protection |
| Elimination |
| Talent |
| Gov Guidance Funds |
| Policy Loans |

| Subsidy Types (6 types) |
|---|
| Non SOE Demand Side Subsidies |
| SOE Demand Side Subsidies |
| Supply Side Subsidies |
| Using Subsidies |
| Infrastructure Subsidies |
| Dump Truck Subsidies |

# Policy instrument classification: evaluation of the model

So how accurate is our model? Is 87% overall accuracy good enough?

| Dataset | qwen(rank16) | glm(rank16) | glm(rank32) | glm(rank8) | Ave |
|---|---|---|---|---|---|
| data | 0.6667 | **0.8374** | 0.8049 | 0.7724 | 0.8049 |
| data_50 | 0.6911 | **0.8780** | 0.8699 | 0.8699 | 0.8726 |
| data_75 | 0.5447 | **0.8780** | 0.8618 | 0.8618 | 0.8672 |
| data_100 | 0.6667 | **0.8455** | 0.7724 | 0.8130 | 0.8103 |
| data_125 | 0.5854 | 0.8455 | 0.8537 | **0.8618** | 0.8537 |
| data_150 | 0.7561 | **0.8780** | 0.8455 | 0.8699 | 0.8645 |

- What's the tradeoff here?
- Validation: keyword search is a reasonable benchmark; wordcloud, misclassification analysis look much more convincing and informative

# Empirical facts

A set of novel estimates that shed light on the political economy of China's IP

- The rotation of city officials is associated with less policy persistence.
  - Paper focuses on lateral move, but why not also test for the **promotion incentive** across the hierarchy?
  - An interesting follow-up question: Is this good innovation or miopic disruption to a more stable long-term policy track?
- Mentioning of an R&D policy is positively correlated with an increase in firm productivity
  - **Implementation** matters, so it would be a missed opportunity not to look at how the effect depends on implementation details

# Interpretation of empirical facts

## How much of the statistically relationship is causal?

- The previous fact is consistent with a possible policy impact, but some omitted variables could be driving the result
  - firm-year level unobservables (e.g., input investment)
  - city-year level unobservables (e.g., local economic cycles)
  - National-level policy waves or campaigns that affect different regions/firms differently
- Policy **pass-through** results cannot be solely explained by the top-down direction.

# Figure 6: Policy Top-down Pass-through