VibePolitics: Complete Research Document

Agentic Unconventional Polling for Public Opinion Shift Detection

Version: 1.0
Date: February 5, 2026
Project Location: Boston, MA
Target: Peer-reviewed publication in political science journals

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Part I: Literature Review

Executive Summary

This literature review surveys academic research on using prediction markets and search behavior data (Google Trends) as alternatives or supplements to traditional polling for election forecasting. The evidence strongly supports the validity of these approaches, with prediction markets often outperforming polls, especially closer to election day. Google Trends shows promise but requires careful methodology. Recent work on LLM-based multi-agent systems for election simulation opens new frontiers directly relevant to VibePolitics.

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1. Prediction Markets for Election Forecasting

1.1 Foundational Work

Wolfers, J., & Zitzewitz, E. (2004). "Prediction Markets." *Journal of Economic Perspectives*, **18(2), 107-126.**

Key Findings:

- Derives theoretical basis from efficient markets hypothesis
- Shows market prices can be interpreted as probability estimates
- Demonstrates that diverse information is efficiently aggregated
- Provides framework for understanding when markets work well

Relevance to VibePolitics: Foundational theory justifying our use of prediction market prices as probability estimates of political outcomes.

Wolfers, J., & Zitzewitz, E. (2006). "Prediction Markets in Theory and Practice." *NBER Working Paper No. 12083*.

Key Findings:

- Comprehensive review of prediction market mechanisms
- Documents historical accuracy across domains (elections, sports, finance)
- Discusses conditions under which markets aggregate information effectively
- Addresses concerns about manipulation and thin markets

Methodology: Meta-analysis of prediction market performance across multiple studies and market types.

Relevance: Establishes scientific legitimacy of prediction markets as forecasting tools. Critical for academic publication strategy.

1.2 Election-Specific Studies

Berg, J.E., Nelson, F.D., & Rietz, T.A. (2008). "Prediction Market Accuracy in the Long Run." *International Journal of Forecasting*, 24(2), 285-300.

Key Findings:

- Iowa Electronic Markets (IEM) data from 1988-2004
- **Markets outperform polls 74% of the time**
- Advantage increases closer to election
- Even small markets with modest liquidity perform well

Methodology: Comparison of IEM vote-share predictions vs. 964 polls across five US presidential elections.

Critical Quote: "Prediction markets are viable election forecasting tools, both in the short run and in the longer run. They outperform the natural alternative, polls, in both dimensions."

Relevance to VibePolitics: Direct empirical support for our core hypothesis. Key citation for methodology section.

Rothschild, D., & Wolfers, J. (2014). "Forecasting Elections: Comparing Prediction Markets, Polls, and Their Biases." *Public Opinion Quarterly*, **78(1), 33-54.**

Key Findings:

- Prediction markets have smaller mean absolute error than polls
- Markets correct faster for house effects and sampling biases
- Polls show systematic biases; markets do not
- Combining markets and polls can improve forecasts

Methodology: Analysis of Intrade prices vs. state-level polls for 2004 and 2008 US presidential elections.

Relevance: Supports multi-source approach. VibePolitics should consider how agent debates could identify and correct for biases.

Sethi, R., Seager, J., Cai, E., Benjamin, D.M., & Morstatter, F. (2021). "Models, Markets, and the Forecasting of Elections." *arXiv:2102.03267.*

Key Findings:

- Examined 2020 US presidential election forecasts
- Both models (538, Economist) and markets (PredictIt) showed overconfidence
- Markets more responsive to late-breaking information
- Suggests value of ensemble approaches

Methodology: Real-time comparison of probabilistic forecasts for battleground states.

Relevance: Recent evidence from a challenging election cycle. Supports VibePolitics approach of using multiple agents with different perspectives.

1.3 Emerging Research on Prediction Markets

Chen, H., Duan, X., El Saddik, A., & Cai, W. (2024). "Political Leanings in Web3 Betting: Decoding the Interplay of Political and Profitable Motives." *arXiv:2407.12345*.

Key Findings:

- Constructed "Political Betting Leaning Score" (PBLS) from Polymarket data
- Analyzed 2024 US Presidential Election betting patterns
- Found evidence of both profit-motivated and politically-motivated trading
- Blockchain transparency enables novel research methodologies

Methodology: On-chain analysis of Polymarket wallet behavior.

Relevance: Directly relevant. Polymarket is one of our primary data sources. This paper validates its use for academic research and provides methodological precedent.

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2. Google Trends for Election Forecasting

2.1 Core Studies

Timoneda, J.C., & Wibbels, E. (2022). "Spikes and Variance: Using Google Trends to Detect and Forecast Protests." *Political Analysis*, **30(1), 1-18.**

Key Findings:

- Novel "variance-in-time" method for Google Trends analysis
- **Spikes in search variance predict political events**
- Method applicable beyond protests to general political forecasting

- Addresses key methodological challenges with GT data

Methodology: Time-series analysis focusing on variance, not just levels.

Relevance: Methodological innovation. VibePolitics agents should track not just search levels but variance/volatility in search patterns—mirrors our approach to market spreads.

Prado-Román, C., & Gómez-Martínez, R. (2021). "Google Trends as a Predictor of Presidential Elections: The United States versus Canada." *American Behavioral Scientist*, **65(4), 508-523.**

Key Findings:

- Analyzed US and Canadian elections 2004-2020
- Google Trends correctly predicted winners in most cases
- Higher search volume associated with electoral success
- Cross-national validity established

Methodology: Regression analysis of search volume indices vs. vote shares.

Relevance: Establishes Google Trends as valid for US political forecasting—our primary focus.

Behnert, J., Lajic, D., & Bauer, P.C. (2024). "Can We Predict Multi-party Elections with Google Trends Data? Evidence Across Elections, Data Windows, and Model Classes." *Journal of Big Data*, **11(1), 1-25.**

Key Findings:

- Systematic test across multiple German elections
- **Google Trends adds predictive value beyond polls alone**
- Best results when combined with polling data
- Model performance varies by election context

Methodology: Machine learning models (random forests, XGBoost) with various feature sets.

Relevance: Supports our multi-source approach. Provides methodological template for combining Google Trends with other data.

3. Multi-Agent Systems & LLMs for Political Forecasting

3.1 LLM-Based Election Simulation

Zhang, X., et al. (2024). "ElectionSim: Massive Population Election Simulation Powered by Large Language Model Driven Agents." *arXiv:2410.20746.*

Key Findings:

- Simulated elections with up to **14,490 LLM agents**
- Agents assigned demographic profiles and political preferences
- Simulation captured opinion dynamics and social influence
- Validated against real election outcomes

Methodology: Large-scale multi-agent simulation with LLM-powered agents.

Relevance: Critical precedent for VibePolitics. Demonstrates feasibility of LLM agents for political simulation. Our architecture is more focused but builds on this foundation.

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4. Research Gaps VibePolitics Addresses

1. **Real-time Multi-source Fusion:** No existing system combines prediction markets + Google Trends + agent reasoning in real-time
2. **Transparent Agent Debate:** Prior work lacks visible reasoning trails
3. **Shift Detection vs. Prediction:** Most research focuses on predicting outcomes; we detect shifts
4. **Continuous Monitoring:** Existing approaches are snapshot-based; we offer continuous tracking

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5. Key Citations for VibePolitics Papers

Must-Cite (Core Literature)

1. Berg, J.E., Nelson, F.D., & Rietz, T.A. (2008). Prediction market accuracy in the long run. *IJF*.
2. Wolfers, J., & Zitzewitz, E. (2004). Prediction markets. *JEP*.
3. Timoneda, J.C., & Wibbels, E. (2022). Spikes and variance: Using Google Trends. *Political Analysis*.
4. Zhang, X., et al. (2024). ElectionSim: Massive population election simulation. *arXiv*.
5. Chen, H., et al. (2024). Political leanings in Web3 betting. *arXiv*.

Part II: Methodology

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1. Core Reframing

We are NOT building: An election forecasting system
We ARE building: A public opinion shift detection system

This distinction is fundamental:

- Forecasting asks: "*Will Candidate X win?*"
- We ask: **"Is something changing in public sentiment, and what is the nature of that change?"**

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2. Available Data Sources

2.1 Polymarket API ⬜ CONFIRMED WORKING

Endpoint: `https://gamma-api.polymarket.com/markets`
Auth: None required

Available Fields:

Field	Type	Use Case
`lastTradePrice`	float	Current probability
`bestBid` / `bestAsk`	float	Order book depth
`spread`	float	Bid-ask spread
`volume24hr`	float	Daily volume
`volume1wk`	float	Weekly volume
`liquidityNum`	float	Market liquidity
`oneDayPriceChange`	float	24h price delta
`oneWeekPriceChange`	float	7d price delta

Limitations:

- No historical tick data (only current snapshot + aggregates)
- No individual trade data
- No order book depth beyond top of book

2.2 Google Trends □ AVAILABLE VIA PYTRENDS

Available Data:

- Interest over time (daily/hourly)
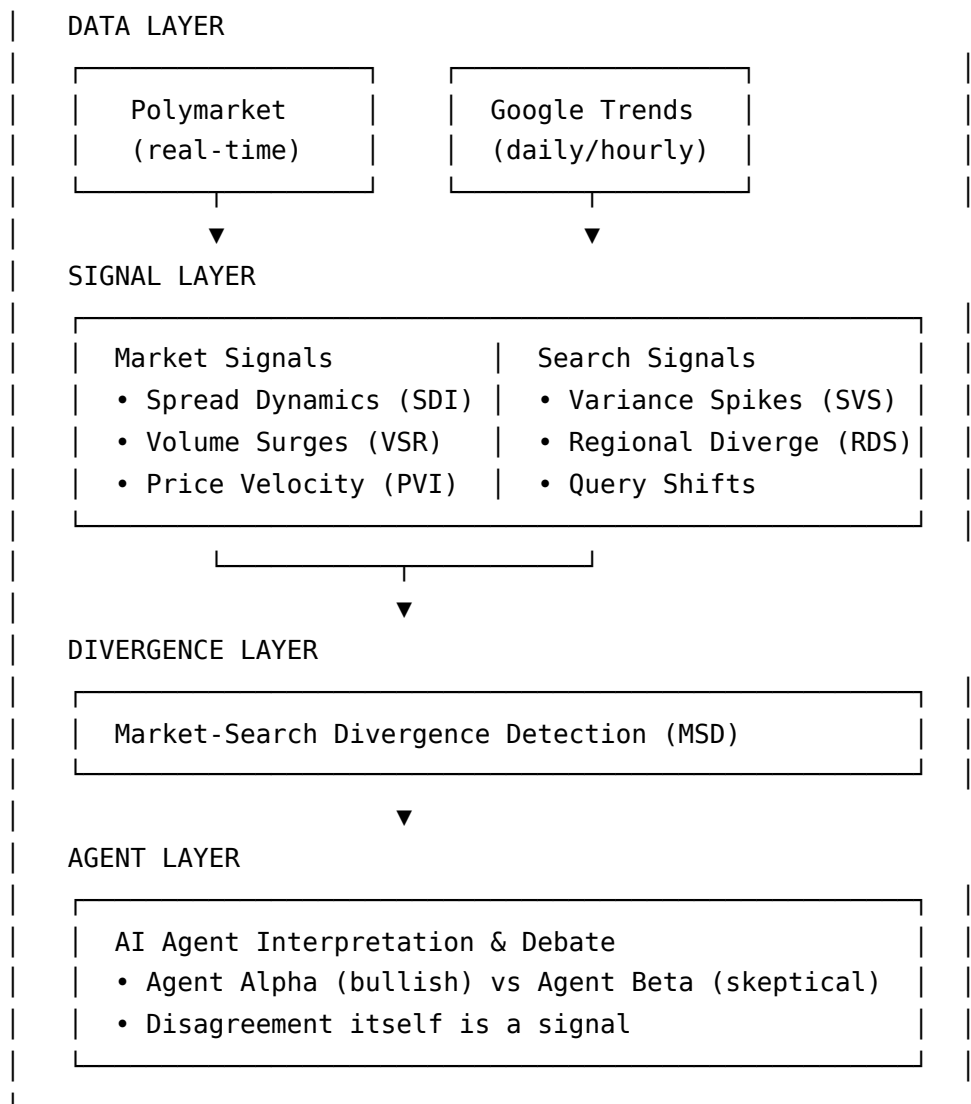- Interest by region (state-level US)
- Related queries and topics

Limitations:

- Normalized 0-100 scale (relative, not absolute)
- Rate limited (~10-20 requests/minute)

2.3 Data Architecture

```
┌─────────────────────────────────────────────┐
│           VIBEPOLITICS SIGNAL FRAMEWORK        │
├─────────────────────────────────────────────┤
```

```
│   DATA LAYER                                              │
│                                                           │
│   ┌─────────────────────┐   ┌─────────────────────┐      │
│   │    Polymarket       │   │   Google Trends     │      │
│   │   (real-time)       │   │   (daily/hourly)    │      │
│   └─────────────────────┘   └─────────────────────┘      │
│            ▼                          ▼                   │
│   SIGNAL LAYER                                            │
│                                                           │
│   ┌────────────────────────────────────────────────┐     │
│   │   Market Signals        │   Search Signals      │     │
│   │   • Spread Dynamics (SDI)│   • Variance Spikes (SVS) │ │
│   │   • Volume Surges (VSR)  │   • Regional Diverge (RDS)│ │
│   │   • Price Velocity (PVI) │   • Query Shifts      │     │
│   └────────────────────────────────────────────────┘     │
│            └──────────────────┬──────────────┘            │
│                               ▼                           │
│   DIVERGENCE LAYER                                        │
│                                                           │
│   ┌────────────────────────────────────────────────┐     │
│   │   Market-Search Divergence Detection (MSD)       │    │
│   └────────────────────────────────────────────────┘     │
│                               ▼                           │
│   AGENT LAYER                                             │
│                                                           │
│   ┌────────────────────────────────────────────────┐     │
│   │   AI Agent Interpretation & Debate               │    │
│   │   • Agent Alpha (bullish) vs Agent Beta (skeptical) │ │
│   │   • Disagreement itself is a signal              │    │
│   └────────────────────────────────────────────────┘     │
│                                                           │
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3. Novel Signal Algorithms

3.1 Spread Dynamics Index (SDI)

Purpose: Detect uncertainty from bid-ask spread changes

```
def spread_dynamics_index(current_spread, historical_spreads):
    mean_spread = np.mean(historical_spreads[-30:])
    std_spread = np.std(historical_spreads[-30:])
    if std_spread == 0:
        return 0
    return (current_spread - mean_spread) / std_spread
```

```
# SDI > 2: Unusual spread widening (uncertainty surge)
# SDI < -2: Unusual spread narrowing (consensus forming)
```

3.2 Volume Surge Ratio (VSR)

Purpose: Detect attention spikes from volume changes

```
def volume_surge_ratio(volume_24hr, volume_1wk):
    daily_avg = volume_1wk / 7
    if daily_avg == 0:
        return 0
    return volume_24hr / daily_avg

# VSR > 3: Volume 3x normal (attention spike)
# VSR > 5: Major event driving volume
```

3.3 Price Velocity Index (PVI)

Purpose: Detect momentum acceleration/reversal

```
def price_velocity_index(change_1d, change_1w):
    weekly_daily_rate = change_1w / 7
    if abs(weekly_daily_rate) < 0.001:
        weekly_daily_rate = 0.001
    return change_1d / abs(weekly_daily_rate)

# PVI > 3: Accelerating momentum
# PVI < -3: Sharp reversal
```

3.4 Search Variance Spike (SVS)

Purpose: Detect erratic search behavior indicating opinion flux
Based on: Timoneda & Wibbels (2022)

```
def search_variance_spike(search_data):
    recent = search_data[-7:]
    baseline = search_data[-30:-7]
    var_recent = np.var(recent)
    var_baseline = np.var(baseline)
```

```
    if var_baseline == 0:
        return 0
    return var_recent / var_baseline


# SVS > 3: Search behavior destabilizing
```

3.5 Regional Divergence Score (RDS)

Purpose: Detect geographic opinion polarization

```
def regional_divergence_score(state_data):
    corr_matrix = np.corrcoef(state_data.T)
    n = corr_matrix.shape[0]
    avg_corr = (np.sum(corr_matrix) - n) / (n * (n - 1))
    return 1 - avg_corr


# RDS > 0.6: States searching very differently
```

3.6 Market-Search Divergence (MSD)

Purpose: Detect information asymmetry between markets and public

```
def market_search_divergence(market_prices, search_volumes):
    z_market = (market_prices - np.mean(market_prices)) / np.std(market_prices)
    z_search = (search_volumes - np.mean(search_volumes)) / np.std(search_volumes
    return np.mean(np.abs(z_market[-7:] - z_search[-7:]))


# MSD > 1.5: Markets and search diverging
```

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4. Agent System Design

4.1 Two-Agent Architecture

Agent Alpha (Bullish Interpreter)

- Looks for signals of momentum, energy, rising attention
- Interprets ambiguous signals optimistically
- Asks: "What would make this a big deal?"

Agent Beta (Skeptical Interpreter)

- Looks for noise, false positives, regression to mean
- Interprets ambiguous signals conservatively
- Asks: "Why might this be nothing?"

4.2 Agent Disagreement as Meta-Signal

When Alpha and Beta disagree significantly → the situation is genuinely ambiguous. This disagreement itself is valuable information.

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5. Signal Classification

Signal Type	Indicators	Interpretation
Attention Surge	High SVS, high VSR	Public focusing on topic
Information Arrival	High SDI (widening), high VPDI	New info being processed
Consensus Formation	Narrowing SDI, low agent disagreement	Opinion crystallizing
Narrative Shift	High RDS	Geographic opinion divergence
Market-Public Gap	High MSD	Information asymmetry

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6. Implementation Timeline

Phase	Weeks	Deliverables
Data Pipeline	1-2	Polymarket + Google Trends collection
Signal Computation	3-4	6 algorithms implemented + backtesting

Phase	Weeks	Deliverables
Agent System	5-6	2-agent interpretation + alerts
Dashboard	7-8	Web UI + real-time display
Validation	9+	Compare to known events, write paper

7. Academic Contribution Claims

1. **First systematic combination** of prediction market signals + Google Trends for opinion shift detection (not prediction)
2. **Novel signal definitions:** SDI, VSR, PVI, SVS, RDS, MSD
3. **Agent disagreement as meta-signal** — novel uncertainty quantification
4. **Shift detection vs. prediction framing** — methodological reframing
5. **Transparent reasoning** — all agent logic logged and auditable

8. Publication Targets

Venue	Focus	Fit
Political Analysis	Methodology	Agent system design, validation
Public Opinion Quarterly	Opinion measurement	Comparison with traditional polls
Journal of Politics	Substantive findings	2026 midterm analysis

References

1. Behnert, J., Lajic, D., & Bauer, P.C. (2024). Can we predict multi-party elections with Google Trends data? *Journal of Big Data*, 11(1).

2. Berg, J.E., Nelson, F.D., & Rietz, T.A. (2008). Prediction market accuracy in the long run. *International Journal of Forecasting*, 24(2), 285-300.
3. Chen, H., et al. (2024). Political leanings in Web3 betting. *arXiv*.
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