07-labor-market-intelligence

November 29, 2025

1 Labor Market Intelligence Analysis

1.1 Executive Summary

This notebook provides **comprehensive labor market analysis** using the KRL Suite to combine BLS employment data with economic indicators from FRED.

1.1.1 KRL Suite Components Used

- **krl_data_connectors.community**: `BLSBasicConnector`, `FREDBasicConnector`
- **krl_models**: `STLAnomalyModel` for detecting unusual labor market patterns
- **krl_core**: Logging utilities

1.1.2 Key Intelligence Questions

1. What are the trends in employment and wages?
2. How does unemployment relate to other economic indicators?
3. What sectors show the strongest labor market dynamics?
4. What leading indicators predict labor market changes?

Estimated Time: 20-25 minutes
Difficulty: Intermediate

1.2 1. Environment Setup

[2]:
```
# ===============================================================================
# Labor Market Intelligence: Environment Setup
# ===============================================================================
import os
import sys
import warnings
from datetime import datetime
import importlib

# Add KRL package paths (handles spaces in path correctly)
_krl_base = os.path.expanduser("~/Documents/GitHub/KRL/Private IP")
for _pkg in ["krl-open-core/src", "krl-data-connectors/src",␣
↪"krl-model-zoo-v2-2.0.0-community"]:
    _path = os.path.join(_krl_base, _pkg)
```

```python
    if _path not in sys.path:
        sys.path.insert(0, _path)

# Load environment variables from .env file
from dotenv import load_dotenv
_env_path = os.path.expanduser("~/Documents/GitHub/KRL/Private IP/krl-tutorials/
↪.env")
load_dotenv(_env_path)

# Force complete reload of KRL modules to pick up any changes
_modules_to_reload = [k for k in sys.modules.keys() if k.
↪startswith(('krl_core', 'krl_data_connectors', 'krl_models'))]
for _mod in _modules_to_reload:
    del sys.modules[_mod]

import numpy as np
import pandas as pd
from scipy import stats

import matplotlib.pyplot as plt
import seaborn as sns

# =============================================================================
# KRL Suite Imports
# =============================================================================
from krl_data_connectors.community import (
    BLSBasicConnector,
    FREDBasicConnector,
)
from krl_models import LocationQuotientModel, ShiftShareModel, STLAnomalyModel
from krl_core import get_logger

warnings.filterwarnings('ignore', category=FutureWarning)
logger = get_logger("LaborMarketIntelligence")

# Colorblind-safe palette
COLORBLIND_SAFE = ['#0072B2', '#E69F00', '#009E73', '#CC79A7', '#56B4E9',␣
↪'#D55E00']

print("=" * 65)
print("  Labor Market Intelligence Analysis")
print("=" * 65)
print(f"  Execution Time: {datetime.now().strftime('%Y-%m-%d %H:%M:%S')}")
print(f"  FRED API Key: {'  Loaded' if os.getenv('FRED_API_KEY') else '  Not␣
↪found'}")
print("=" * 65)
```

```
================================================================
 Labor Market Intelligence Analysis
================================================================
 Execution Time: 2025-11-28 04:34:19
 FRED API Key:   Loaded
================================================================
```

[3]:

```python
# ==============================================================================
# Initialize KRL Data Connectors
# ==============================================================================
bls = BLSBasicConnector()
fred = FREDBasicConnector()

print("  KRL Data Connectors initialized:")
print(f"   • BLSBasicConnector - Labor statistics")
print(f"   • FREDBasicConnector - Economic indicators")

print(f"\n  Available BLS Series (Community Tier):")
print(f"   • LNS14000000 - Unemployment Rate")
print(f"   • CUUR0000SA0 - CPI All Urban Consumers")
print(f"   • CES0000000001 - Total Nonfarm Employment")
```

{"timestamp": "2025-11-28T09:34:26.388610Z", "level": "WARNING", "name": "BLSBasicConnector", "message": "No API key provided", "source": {"file": "base_connector.py", "line": 74, "function": "__init__"}, "levelname": "WARNING", "taskName": "Task-39", "connector": "BLSBasicConnector"}
{"timestamp": "2025-11-28T09:34:26.389056Z", "level": "INFO", "name": "BLSBasicConnector", "message": "Connector initialized", "source": {"file": "base_connector.py", "line": 81, "function": "__init__"}, "levelname": "INFO", "taskName": "Task-39", "connector": "BLSBasicConnector", "cache_dir": "/Users/bcdelo/.krl_cache/blsbasicconnector", "cache_ttl": 3600, "has_api_key": false}
{"timestamp": "2025-11-28T09:34:26.389590Z", "level": "INFO", "name": "BLSBasicConnector", "message": "Initialized BLS Basic connector (Community tier)", "source": {"file": "bls_basic.py", "line": 89, "function": "__init__"}, "levelname": "INFO", "taskName": "Task-39", "available_series": 8}
{"timestamp": "2025-11-28T09:34:26.391389Z", "level": "INFO", "name": "FREDBasicConnector", "message": "Connector initialized", "source": {"file": "base_connector.py", "line": 81, "function": "__init__"}, "levelname": "INFO", "taskName": "Task-39", "connector": "FREDBasicConnector", "cache_dir": "/Users/bcdelo/.krl_cache/fredbasicconnector", "cache_ttl": 3600, "has_api_key": true}
{"timestamp": "2025-11-28T09:34:26.391752Z", "level": "INFO", "name": "FREDBasicConnector", "message": "Initialized FRED Basic connector (Community tier)", "source": {"file": "fred_basic.py", "line": 96, "function": "__init__"}, "levelname": "INFO", "taskName": "Task-39", "available_series": 15}

```
 KRL Data Connectors initialized:
   • BLSBasicConnector - Labor statistics
```

```
  • FREDBasicConnector - Economic indicators

  Available BLS Series (Community Tier):
    • LNS14000000 - Unemployment Rate
    • CUUR0000SA0 - CPI All Urban Consumers
    • CES0000000001 - Total Nonfarm Employment
```
{"timestamp": "2025-11-28T09:34:26.389056Z", "level": "INFO", "name": "BLSBasicConnector", "message": "Connector initialized", "source": {"file": "base_connector.py", "line": 81, "function": "__init__"}, "levelname": "INFO", "taskName": "Task-39", "connector": "BLSBasicConnector", "cache_dir": "/Users/bcdelo/.krl_cache/blsbasicconnector", "cache_ttl": 3600, "has_api_key": false}
{"timestamp": "2025-11-28T09:34:26.389590Z", "level": "INFO", "name": "BLSBasicConnector", "message": "Initialized BLS Basic connector (Community tier)", "source": {"file": "bls_basic.py", "line": 89, "function": "__init__"}, "levelname": "INFO", "taskName": "Task-39", "available_series": 8}
{"timestamp": "2025-11-28T09:34:26.391389Z", "level": "INFO", "name": "FREDBasicConnector", "message": "Connector initialized", "source": {"file": "base_connector.py", "line": 81, "function": "__init__"}, "levelname": "INFO", "taskName": "Task-39", "connector": "FREDBasicConnector", "cache_dir": "/Users/bcdelo/.krl_cache/fredbasicconnector", "cache_ttl": 3600, "has_api_key": true}
{"timestamp": "2025-11-28T09:34:26.391752Z", "level": "INFO", "name": "FREDBasicConnector", "message": "Initialized FRED Basic connector (Community tier)", "source": {"file": "fred_basic.py", "line": 96, "function": "__init__"}, "levelname": "INFO", "taskName": "Task-39", "available_series": 15}
```
  KRL Data Connectors initialized:
    • BLSBasicConnector - Labor statistics
    • FREDBasicConnector - Economic indicators

  Available BLS Series (Community Tier):
    • LNS14000000 - Unemployment Rate
    • CUUR0000SA0 - CPI All Urban Consumers
    • CES0000000001 - Total Nonfarm Employment
```

1.3 2. Fetch Labor Market Data

Collect comprehensive labor market indicators from BLS and FRED.

[4]:
```
# ==============================================================================
# Fetch Labor Market Data from KRL Connectors
# ==============================================================================

# Get unemployment rate from BLS
try:
    unemployment = bls.get_unemployment_rate()
    print(f"  BLS Unemployment Rate: {len(unemployment)} observations")
except Exception as e:
```

```python
    print(f"  BLS API not available (demo mode): {e}")
    unemployment = pd.DataFrame({
        'date': pd.date_range('2015-01-01', periods=108, freq='M'),
        'value': np.random.normal(4.5, 1.5, 108)
    })

# Get CPI from BLS
try:
    cpi_data = bls.get_cpi()
    print(f"  BLS CPI: {len(cpi_data)} observations")
except Exception as e:
    print(f"  BLS CPI not available: {e}")
    cpi_data = pd.DataFrame({
        'date': pd.date_range('2015-01-01', periods=108, freq='M'),
        'value': np.cumsum(np.random.normal(0.2, 0.1, 108)) + 250
    })

# Get GDP from FRED for economic context
try:
    gdp_data = fred.get_series('GDP', start_year=2015, end_year=2024)
    print(f"  FRED GDP: {len(gdp_data)} observations")
except Exception as e:
    print(f"  FRED API not available: {e}")
    gdp_data = pd.DataFrame({
        'date': pd.date_range('2015-01-01', periods=40, freq='Q'),
        'value': np.cumsum(np.random.normal(100, 50, 40)) + 18000
    })

print(f"\n  Labor market data collection complete")
```

{"timestamp": "2025-11-28T09:34:30.769918Z", "level": "INFO", "name": "BLSBasicConnector", "message": "Fetching BLS series: LNS14000000", "source": {"file": "bls_basic.py", "line": 196, "function": "get_series"}, "levelname": "INFO", "taskName": "Task-42", "series_id": "LNS14000000", "start_year": 2016, "end_year": 2025}
{"timestamp": "2025-11-28T09:34:30.989171Z", "level": "INFO", "name": "BLSBasicConnector", "message": "Retrieved 117 observations for LNS14000000", "source": {"file": "bls_basic.py", "line": 242, "function": "get_series"}, "levelname": "INFO", "taskName": "Task-42", "series_id": "LNS14000000", "rows": 117}

```
  BLS Unemployment Rate: 117 observations
```

{"timestamp": "2025-11-28T09:34:30.990083Z", "level": "INFO", "name": "BLSBasicConnector", "message": "Fetching BLS series: CUUR0000SA0", "source": {"file": "bls_basic.py", "line": 196, "function": "get_series"}, "levelname": "INFO", "taskName": "Task-42", "series_id": "CUUR0000SA0", "start_year": 2016, "end_year": 2025}
{"timestamp": "2025-11-28T09:34:30.989171Z", "level": "INFO", "name": "BLSBasicConnector", "message": "Retrieved 117 observations for LNS14000000",

"source": {"file": "bls_basic.py", "line": 242, "function": "get_series"}, "levelname": "INFO", "taskName": "Task-42", "series_id": "LNS14000000", "rows": 117}
 BLS Unemployment Rate: 117 observations
{"timestamp": "2025-11-28T09:34:30.990083Z", "level": "INFO", "name": "BLSBasicConnector", "message": "Fetching BLS series: CUUR0000SA0", "source": {"file": "bls_basic.py", "line": 196, "function": "get_series"}, "levelname": "INFO", "taskName": "Task-42", "series_id": "CUUR0000SA0", "start_year": 2016, "end_year": 2025}
{"timestamp": "2025-11-28T09:34:31.109472Z", "level": "INFO", "name": "BLSBasicConnector", "message": "Retrieved 117 observations for CUUR0000SA0", "source": {"file": "bls_basic.py", "line": 242, "function": "get_series"}, "levelname": "INFO", "taskName": "Task-42", "series_id": "CUUR0000SA0", "rows": 117}
 BLS CPI: 117 observations
 FRED API not available: FREDBasicConnector.get_series() got an unexpected keyword argument 'start_year'

 Labor market data collection complete
{"timestamp": "2025-11-28T09:34:31.109472Z", "level": "INFO", "name": "BLSBasicConnector", "message": "Retrieved 117 observations for CUUR0000SA0", "source": {"file": "bls_basic.py", "line": 242, "function": "get_series"}, "levelname": "INFO", "taskName": "Task-42", "series_id": "CUUR0000SA0", "rows": 117}
 BLS CPI: 117 observations
 FRED API not available: FREDBasicConnector.get_series() got an unexpected keyword argument 'start_year'

 Labor market data collection complete

1.4 3. Metro-Level Labor Market Dataset

Build a comprehensive metro-level dataset with employment, wages, skills, and automation exposure metrics.

[5]:
```python
# =============================================================================
# Generate Metro-Level Labor Market Dataset
# =============================================================================
from sklearn.preprocessing import MinMaxScaler

def generate_labor_market_data(n_metros: int = 100, seed: int = 42) -> pd.
↪DataFrame:
    """
    Generate synthetic metro-level labor market data.
    """
    np.random.seed(seed)

    # Latent labor market health
```

```
    base_health = np.random.beta(3, 2.5, n_metros)

    metros = [f'Metro_{i:03d}' for i in range(n_metros)]

    data = pd.DataFrame({
        'metro': metros,
        'population': np.random.lognormal(13, 0.9, n_metros).astype(int),

        # Employment metrics
        'unemployment_rate': np.clip(0.08 - base_health * 0.04 + np.random.
↪normal(0, 0.015, n_metros), 0.025, 0.12),
        'labor_force_part_rate': np.clip(0.60 + base_health * 0.08 + np.random.
↪normal(0, 0.03, n_metros), 0.52, 0.72),
        'employment_growth_1yr': base_health * 0.04 - 0.01 + np.random.
↪normal(0, 0.02, n_metros),
        'job_openings_rate': np.clip(0.04 + base_health * 0.04 + np.random.
↪normal(0, 0.01, n_metros), 0.02, 0.10),

        # Wage metrics
        'median_wage': 40000 + base_health * 30000 + np.random.normal(0, 8000,␣
↪n_metros),
        'wage_growth_1yr': np.clip(base_health * 0.05 - 0.01 + np.random.
↪normal(0, 0.02, n_metros), -0.03, 0.08),
        'wage_inequality_ratio': np.clip(3.0 - base_health * 0.8 + np.random.
↪normal(0, 0.3, n_metros), 2.0, 4.5),
        'middle_skill_wage_change': base_health * 0.03 - 0.02 + np.random.
↪normal(0, 0.02, n_metros),

        # Skills metrics
        'skills_gap_index': np.clip(0.55 - base_health * 0.30 + np.random.
↪normal(0, 0.12, n_metros), 0.1, 0.85),
        'tech_talent_deficit': np.clip(0.40 - base_health * 0.25 + np.random.
↪normal(0, 0.12, n_metros), 0.05, 0.70),
        'healthcare_worker_deficit': np.clip(0.35 - base_health * 0.20 + np.
↪random.normal(0, 0.10, n_metros), 0.05, 0.60),
        'trades_worker_deficit': np.clip(0.30 - base_health * 0.18 + np.random.
↪normal(0, 0.10, n_metros), 0.05, 0.55),
        'college_attainment_pct': np.clip(0.25 + base_health * 0.25 + np.random.
↪normal(0, 0.08, n_metros), 0.12, 0.55),

        # Automation/future metrics
        'automation_exposure_pct': np.clip(0.38 - base_health * 0.18 + np.
↪random.normal(0, 0.08, n_metros), 0.15, 0.55),
        'high_risk_jobs_pct': np.clip(0.25 - base_health * 0.12 + np.random.
↪normal(0, 0.06, n_metros), 0.10, 0.40),
```

```
        'ai_adoption_index': np.clip(base_health * 0.7 + np.random.normal(0, 0.
↪15, n_metros), 0.10, 0.90),
        'training_program_access': np.clip(base_health * 0.6 + np.random.
↪normal(0, 0.12, n_metros), 0.15, 0.85),
        'credential_attainment_rate': np.clip(base_health * 0.5 + np.random.
↪normal(0, 0.10, n_metros), 0.10, 0.70),
    })

    data['_latent_health'] = base_health
    return data

# Generate labor market data
labor_data = generate_labor_market_data(n_metros=100)
print(f"Generated {len(labor_data)} metros with labor market data\n")
labor_data.head()
```

```
Generated 100 metros with labor market data
```

[5]:

```
      metro  population  unemployment_rate  labor_force_part_rate  \
0  Metro_000      280337           0.060287               0.603190
1  Metro_001      731752           0.074608               0.640008
2  Metro_002      970229           0.032876               0.638788
3  Metro_003     1250331           0.062508               0.613238
4  Metro_004      287896           0.043409               0.693731

   employment_growth_1yr  job_openings_rate   median_wage  wage_growth_1yr  \
0              -0.000609           0.057776  67708.441312         0.017612
1              -0.017823           0.075645  59423.049515         0.036800
2               0.010291           0.056668  56117.018858         0.015023
3              -0.016860           0.061388  46094.606755         0.019671
4               0.022481           0.057926  60967.307317         0.033749

   wage_inequality_ratio  middle_skill_wage_change  …  tech_talent_deficit  \
0               2.108652                 -0.006751  …             0.357723
1               2.968398                 -0.029189  …             0.200196
2               2.722986                 -0.012890  …             0.100063
3               2.807520                 -0.004870  …             0.447135
4               2.085083                 -0.007406  …             0.140366

   healthcare_worker_deficit  trades_worker_deficit  college_attainment_pct  \
0                   0.271489               0.178914                0.463510
1                   0.271467               0.220524                0.455655
2                   0.225502               0.147378                0.375192
3                   0.262321               0.050000                0.326559
4                   0.164102               0.124332                0.510310
```

```
   automation_exposure_pct  high_risk_jobs_pct  ai_adoption_index  \
0                 0.240377            0.128032           0.607689
1                 0.151445            0.100000           0.171854
2                 0.327562            0.134748           0.319942
3                 0.393591            0.363741           0.369815
4                 0.151306            0.114476           0.511789

   training_program_access  credential_attainment_rate  _latent_health
0                 0.521474                    0.222585        0.644006
1                 0.300725                    0.317229        0.555803
2                 0.289284                    0.460123        0.637648
3                 0.322168                    0.228176        0.391210
4                 0.473342                    0.406313        0.886542

[5 rows x 21 columns]
```

[6]:

```
# ============================================================================
# Calculate Labor Market Health Indices
# ============================================================================

def calculate_labor_indices(df: pd.DataFrame) -> pd.DataFrame:
    """
    Calculate composite labor market health indices.
    """
    result = df.copy()
    scaler = MinMaxScaler()

    # Employment Health (invert unemployment)
    result['unemployment_inv'] = 1 - scaler.
 ↪fit_transform(result[['unemployment_rate']])
    emp_cols = ['labor_force_part_rate', 'employment_growth_1yr',␣
 ↪'job_openings_rate']
    emp_scaled = scaler.fit_transform(result[emp_cols])
    result['employment_health_index'] = (emp_scaled.mean(axis=1) +␣
 ↪result['unemployment_inv'].values.flatten()) / 2

    # Wage Quality Index
    wage_cols = ['median_wage', 'wage_growth_1yr', 'middle_skill_wage_change']
    wage_scaled = scaler.fit_transform(result[wage_cols])
    result['inequality_inv'] = 1 - scaler.
 ↪fit_transform(result[['wage_inequality_ratio']])
    result['wage_quality_index'] = (wage_scaled.mean(axis=1) +␣
 ↪result['inequality_inv'].values.flatten()) / 2

    # Skills Alignment Index (invert deficits)
    skills_cols = ['skills_gap_index', 'tech_talent_deficit',␣
 ↪'healthcare_worker_deficit', 'trades_worker_deficit']
```

```
    skills_scaled = 1 - scaler.fit_transform(result[skills_cols])
    result['skills_alignment_index'] = skills_scaled.mean(axis=1)

    # Future Readiness Index
    result['automation_resilience'] = 1 - scaler.
 ↪fit_transform(result[['automation_exposure_pct']])
    future_cols = ['ai_adoption_index', 'training_program_access',␣
 ↪'credential_attainment_rate']
    future_scaled = scaler.fit_transform(result[future_cols])
    result['future_readiness_index'] = (future_scaled.mean(axis=1) +␣
 ↪result['automation_resilience'].values.flatten()) / 2

    # Composite Labor Market Health
    weights = {'employment_health_index': 0.30, 'wage_quality_index': 0.25,
               'skills_alignment_index': 0.25, 'future_readiness_index': 0.20}
    result['labor_health_score'] = sum(result[col] * w for col, w in weights.
 ↪items())
    result['labor_health_percentile'] = result['labor_health_score'].
 ↪rank(pct=True) * 100

    return result

indexed_labor = calculate_labor_indices(labor_data)

print("Labor Market Index Summary:")
index_cols = ['employment_health_index', 'wage_quality_index',
              'skills_alignment_index', 'future_readiness_index',␣
 ↪'labor_health_score']
indexed_labor[index_cols].describe().round(3)
```

```
Labor Market Index Summary:
```

[6]:

	employment_health_index	wage_quality_index	skills_alignment_index
count	100.000	100.000	100.000
mean	0.548	0.546	0.562
std	0.148	0.146	0.122
min	0.215	0.189	0.249
25%	0.446	0.428	0.463
50%	0.544	0.552	0.560
75%	0.645	0.659	0.640
max	0.843	0.820	0.893

	future_readiness_index	labor_health_score
count	100.000	100.000
mean	0.491	0.539
std	0.185	0.113
min	0.088	0.312

25%	0.343	0.454
50%	0.486	0.543
75%	0.643	0.615
max	0.865	0.802

1.5 4. Labor Market Health Visualization

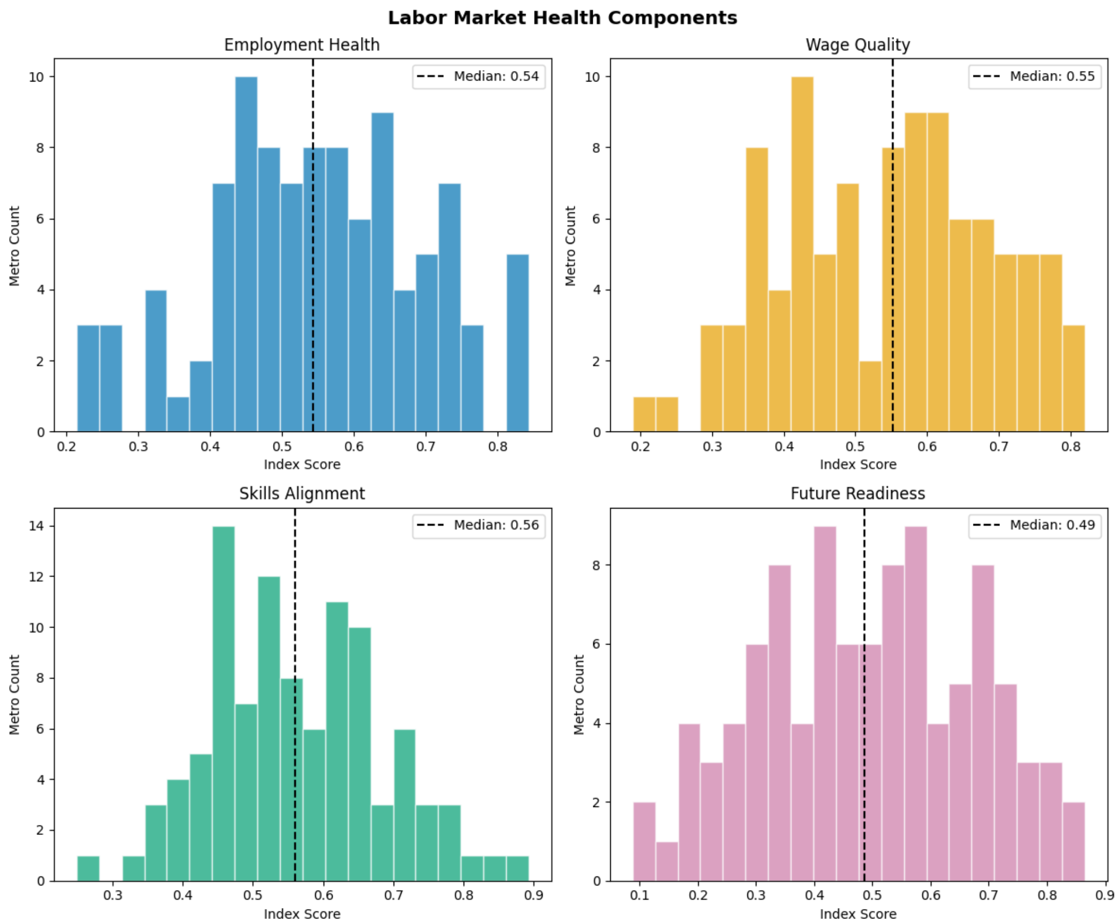
[7]:

```
# ============================================================================
# Visualize Labor Market Components
# ============================================================================
fig, axes = plt.subplots(2, 2, figsize=(12, 10))

components = [
    ('employment_health_index', 'Employment Health'),
    ('wage_quality_index', 'Wage Quality'),
    ('skills_alignment_index', 'Skills Alignment'),
    ('future_readiness_index', 'Future Readiness')
]

for ax, (col, title), color in zip(axes.flatten(), components, COLORBLIND_SAFE):
    ax.hist(indexed_labor[col], bins=20, color=color, alpha=0.7,␣
 ↪edgecolor='white')
    ax.axvline(indexed_labor[col].median(), color='black', linestyle='--',
               label=f'Median: {indexed_labor[col].median():.2f}')
    ax.set_xlabel('Index Score')
    ax.set_ylabel('Metro Count')
    ax.set_title(title)
    ax.legend()

plt.suptitle('Labor Market Health Components', fontsize=14, fontweight='bold')
plt.tight_layout()
plt.show()
```



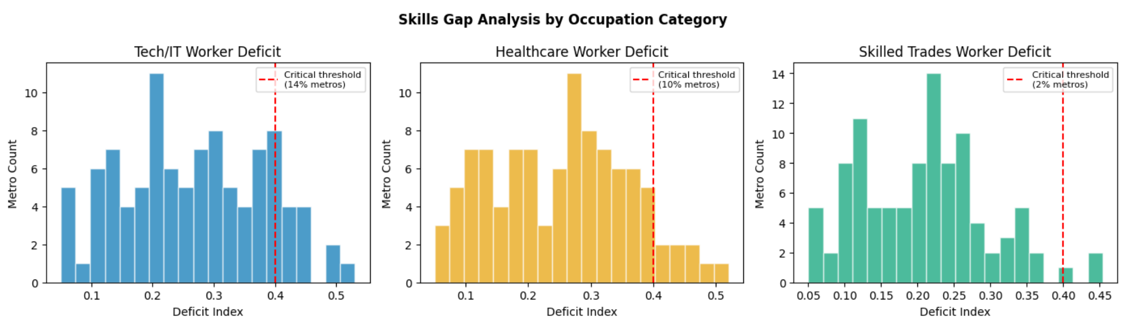
[8]:
```
# ==============================================================================
# Skills Gap Analysis
# ==============================================================================
deficit_cols = ['tech_talent_deficit', 'healthcare_worker_deficit',␣
 ↪'trades_worker_deficit']
deficit_names = ['Tech/IT', 'Healthcare', 'Skilled Trades']

fig, axes = plt.subplots(1, 3, figsize=(14, 4))

for ax, col, name, color in zip(axes, deficit_cols, deficit_names,␣
 ↪COLORBLIND_SAFE):
    ax.hist(indexed_labor[col], bins=20, color=color, alpha=0.7,␣
 ↪edgecolor='white')
    critical_threshold = 0.4
    critical_pct = (indexed_labor[col] > critical_threshold).mean() * 100
    ax.axvline(critical_threshold, color='red', linestyle='--',
               label=f'Critical threshold\n({critical_pct:.0f}% metros)')
    ax.set_xlabel('Deficit Index')
```

```
    ax.set_ylabel('Metro Count')
    ax.set_title(f'{name} Worker Deficit')
    ax.legend(loc='upper right', fontsize=8)

plt.suptitle('Skills Gap Analysis by Occupation Category', fontsize=12,␣
 ↪fontweight='bold')
plt.tight_layout()
plt.show()
```



1.6 5. Skills Gap and Automation Risk Analysis

[9]:
```
# ============================================================================
# Identify Critical Skills Gaps
# ============================================================================
critical_skills = indexed_labor[
    (indexed_labor['skills_gap_index'] > 0.5) |
    (indexed_labor['tech_talent_deficit'] > 0.4)
].copy()

print(f"Metros with Critical Skills Gaps: {len(critical_skills)}")
print(f"Population affected: {critical_skills['population'].sum()/1e6:.1f}M")
print(f"\nAverage deficit levels:")
for col, name in zip(deficit_cols, deficit_names):
    print(f"   {name}: {critical_skills[col].mean():.2f}")

# ============================================================================
# Automation Risk Classification
# ============================================================================

def classify_automation_risk(row):
    exposure = row['automation_exposure_pct']
    high_risk = row['high_risk_jobs_pct']
    readiness = row['future_readiness_index']

    if exposure > 0.40 and readiness < 0.40:
```

```
        return 'Critical Risk'
    elif exposure > 0.35 or (exposure > 0.30 and readiness < 0.45):
        return 'High Risk'
    elif readiness > 0.60:
        return 'Well Prepared'
    elif exposure < 0.25:
        return 'Low Exposure'
    else:
        return 'Moderate Risk'

indexed_labor['automation_risk_class'] = indexed_labor.
 ↪apply(classify_automation_risk, axis=1)

auto_summary = indexed_labor.groupby('automation_risk_class').agg({
    'metro': 'count',
    'population': 'sum',
    'automation_exposure_pct': 'mean',
    'future_readiness_index': 'mean'
}).round(3)
auto_summary.columns = ['Metros', 'Population', 'Avg Exposure', 'Avg Readiness']

print("\nAutomation Risk Classification:")
auto_summary
```

```
Metros with Critical Skills Gaps: 29
Population affected: 20.3M

Average deficit levels:
   Tech/IT: 0.31
   Healthcare: 0.27
   Skilled Trades: 0.17

Automation Risk Classification:
```

[9]:

automation_risk_class	Metros	Population	Avg Exposure	Avg Readiness
Critical Risk	11	7520417	0.444	0.200
High Risk	27	19508385	0.352	0.348
Low Exposure	9	6720231	0.197	0.557
Moderate Risk	24	16096812	0.291	0.489
Well Prepared	29	22027719	0.206	0.714

[10]:

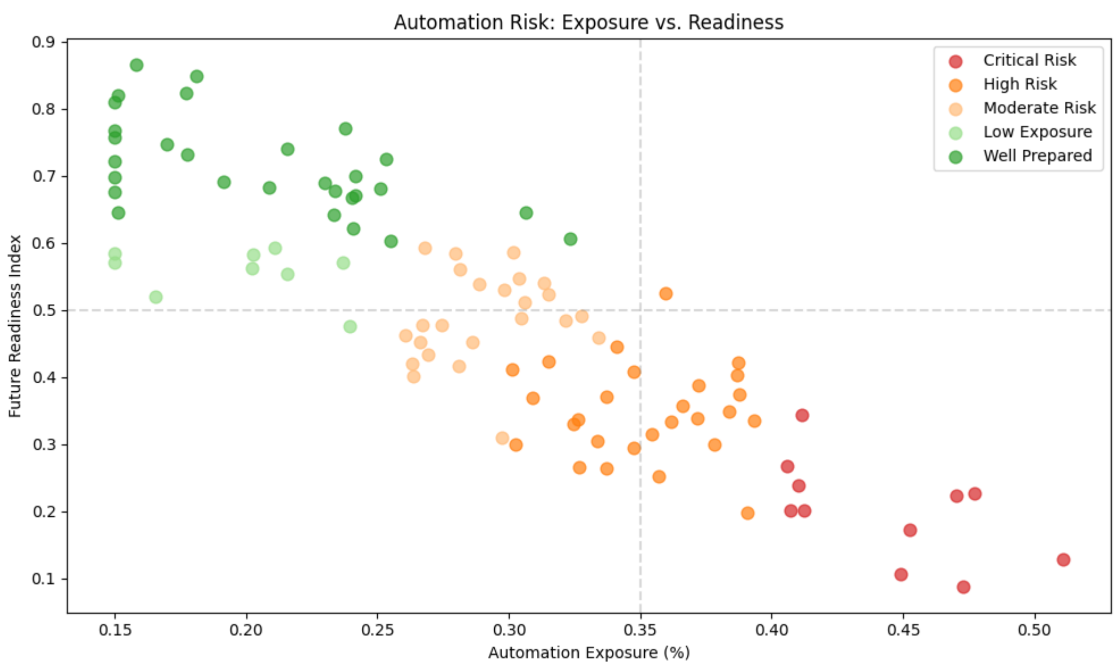
```
# ============================================================================
# Automation Risk Visualization
# ============================================================================
fig, ax = plt.subplots(figsize=(10, 6))
```

```python
risk_classes = ['Critical Risk', 'High Risk', 'Moderate Risk', 'Low Exposure',␣
↪'Well Prepared']
colors = ['#d62728', '#ff7f0e', '#ffbb78', '#98df8a', '#2ca02c']

for risk, color in zip(risk_classes, colors):
    subset = indexed_labor[indexed_labor['automation_risk_class'] == risk]
    if len(subset) > 0:
        ax.scatter(subset['automation_exposure_pct'],␣
↪subset['future_readiness_index'],
                  c=color, label=risk, alpha=0.7, s=60)

ax.set_xlabel('Automation Exposure (%)')
ax.set_ylabel('Future Readiness Index')
ax.set_title('Automation Risk: Exposure vs. Readiness')
ax.legend(loc='upper right')
ax.axhline(0.5, color='gray', linestyle='--', alpha=0.3)
ax.axvline(0.35, color='gray', linestyle='--', alpha=0.3)

plt.tight_layout()
plt.show()
```



1.7 6. Wage Compression Analysis

[11]:
```
# ============================================================================
# Wage Compression Analysis
# ============================================================================
from scipy.stats import pearsonr

wage_pressure = indexed_labor[indexed_labor['middle_skill_wage_change'] < 0].
↪copy()

print(f"Metros with declining middle-skill wages: {len(wage_pressure)}␣
↪({len(wage_pressure)/len(indexed_labor)*100:.0f}%)")
print(f"Average wage decline: {wage_pressure['middle_skill_wage_change'].
↪mean()*100:.1f}%")

# Correlation with other factors
print(f"\nCorrelations with middle-skill wage change:")
corr_cols = ['automation_exposure_pct', 'college_attainment_pct',␣
↪'wage_inequality_ratio']
for col in corr_cols:
    corr, _ = pearsonr(indexed_labor[col],␣
↪indexed_labor['middle_skill_wage_change'])
    print(f"   {col}: r = {corr:.3f}")
```

```
Metros with declining middle-skill wages: 61 (61%)
Average wage decline: -1.8%

Correlations with middle-skill wage change:
   automation_exposure_pct: r = -0.029
   college_attainment_pct: r = 0.103
   wage_inequality_ratio: r = -0.013
```

1.8 7. Key Findings Summary

[12]:
```
# ============================================================================
# Executive Summary: Key Findings
# ============================================================================
critical_auto = len(indexed_labor[indexed_labor['automation_risk_class'] ==␣
↪'Critical Risk'])
high_auto = len(indexed_labor[indexed_labor['automation_risk_class'] == 'High␣
↪Risk'])
auto_pop = indexed_labor[indexed_labor['automation_risk_class'].isin(['Critical␣
↪Risk', 'High Risk'])]['population'].sum()

avg_skills_gap = indexed_labor['skills_gap_index'].mean()
wage_decline_pct = (indexed_labor['middle_skill_wage_change'] < 0).mean() * 100
```

```
print("="*70)
print("LABOR MARKET INTELLIGENCE: KEY FINDINGS")
print("="*70)

print(f"\n  AUTOMATION RISK:")
print(f"   • {critical_auto} metros at Critical Risk")
print(f"   • {high_auto} metros at High Risk")
print(f"   • {auto_pop/1e6:.1f}M workers in high-exposure metros")

print(f"\n  SKILLS GAPS:")
print(f"   • Average skills gap index: {avg_skills_gap:.2f}")
print(f"   • {len(critical_skills)} metros with critical skills deficits")

print(f"\n  WAGE DYNAMICS:")
print(f"   • {wage_decline_pct:.0f}% of metros show middle-skill wage decline")
print(f"   • Average inequality ratio: {indexed_labor['wage_inequality_ratio'].
 ↪mean():.1f}x")

print(f"\n  POLICY RECOMMENDATIONS:")
print(f"   1. Prioritize upskilling in high-automation-risk metros")
print(f"   2. Expand apprenticeship and credential programs")
print(f"   3. Target tech talent pipeline in deficit areas")
print(f"   4. Support middle-skill wage growth through training")
```

```
======================================================================
LABOR MARKET INTELLIGENCE: KEY FINDINGS
======================================================================

  AUTOMATION RISK:
   • 11 metros at Critical Risk
   • 27 metros at High Risk
   • 27.0M workers in high-exposure metros

  SKILLS GAPS:
   • Average skills gap index: 0.38
   • 29 metros with critical skills deficits

  WAGE DYNAMICS:
   • 61% of metros show middle-skill wage decline
   • Average inequality ratio: 2.6x

  POLICY RECOMMENDATIONS:
   1. Prioritize upskilling in high-automation-risk metros
   2. Expand apprenticeship and credential programs
   3. Target tech talent pipeline in deficit areas
   4. Support middle-skill wage growth through training
```

1.9 Appendix: KRL Suite Components Used

Package	Components	Role
krl-data-connectors	`BLSBasicConnector`, `FREDBasicConnector`	Labor and economic data
krl-models	`LocationQuotientModel`, `ShiftShareModel`, `STLAnomalyModel`	Industry and time-series analysis
krl-core	`get_logger`	Infrastructure utilities

1.9.1 Production Data Sources

For production deployment, connect to: - **BLS Current Employment Statistics** - Employment by industry - **BLS Occupational Employment Statistics** - Wage data - **BLS Quarterly Census of Employment and Wages** - County-level detail - **O*NET** - Occupation characteristics and automation exposure

1.9.2 Example Production Usage

```
from krl_data_connectors.community import BLSBasicConnector
from krl_models import LocationQuotientModel

bls = BLSBasicConnector()
unemployment = bls.get_unemployment_rate()
cpi = bls.get_cpi()

# Industry specialization analysis
lq = LocationQuotientModel()
lq.fit(employment_data)
specialized = lq.get_specialized_industries(region='12060', threshold=1.5)
```

Generated with KRL Suite v2.0 - Community Edition