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# THE IMPACT OF LARGE LANGUAGE MODELS ON THE LABOUR MARKET: SPATIAL EVIDENCE FROM JOB ADS IN HUNGARY

The Impact of AI on the Macroeconomy and Monetary Policy: Joint conference of ESCB ChaMP Research Network and BdE

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*With thanks to Malatinszky Gábor (MNB)

# OVERVIEW OF RESULTS

- 10% of workload could be substituted by LLMs that are at least twice as fast as humans and without a negative impact on quality. In the US this is 15%.
- LLMs are complementary for all job ads. Rarely does exposure exceed 30 per cent.
- Spatial differences in exposure: Of the factors investigated it is industry mix that matters the most. Positive correlation between LLM exposure on the one hand and proportion of young adults or share of population living in cities, on the other.

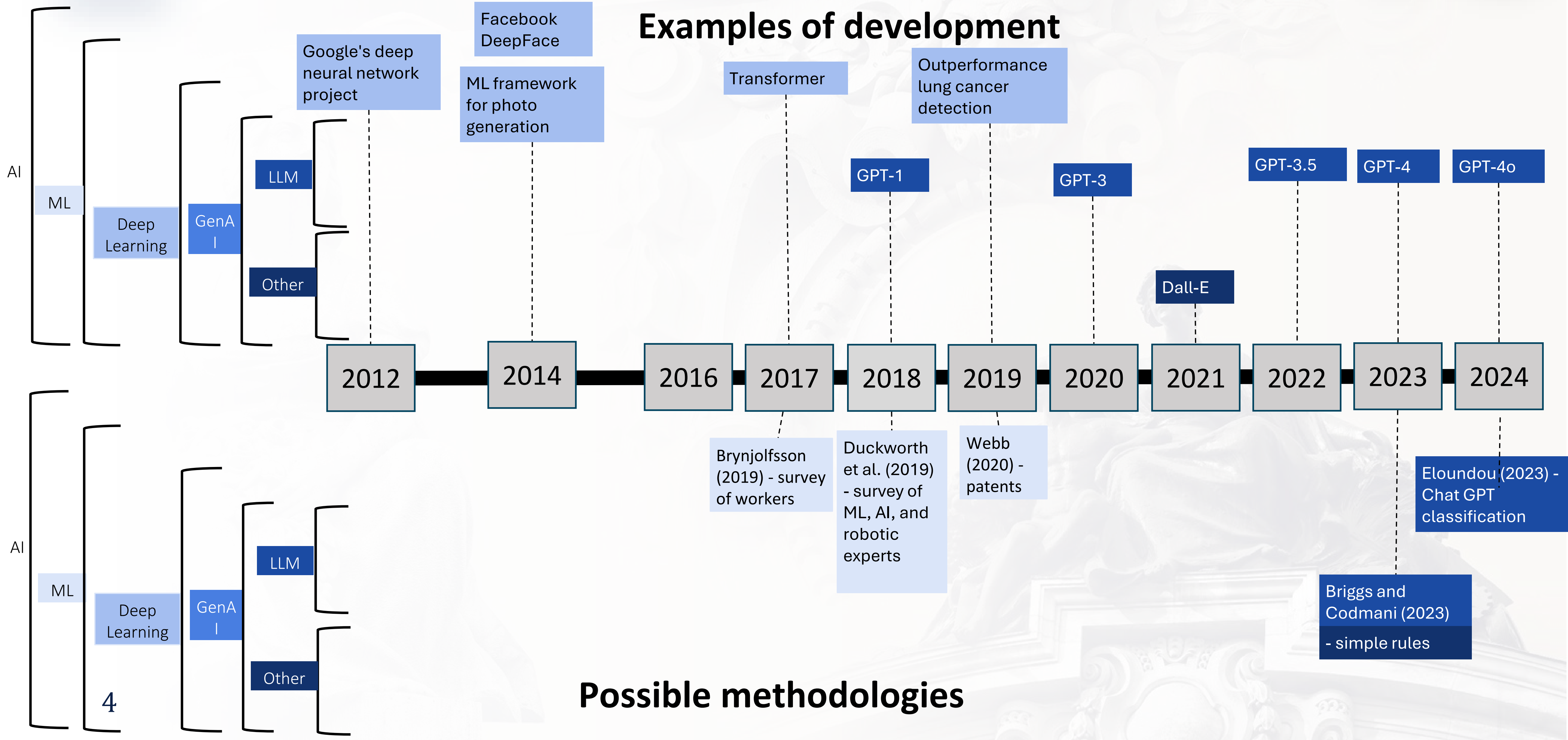
# RESEARCH QUESTIONS

- What portion of current job vacancy work could be substituted by AI?
- What are the spatial patterns? What factors are the spatial patterns associated with?

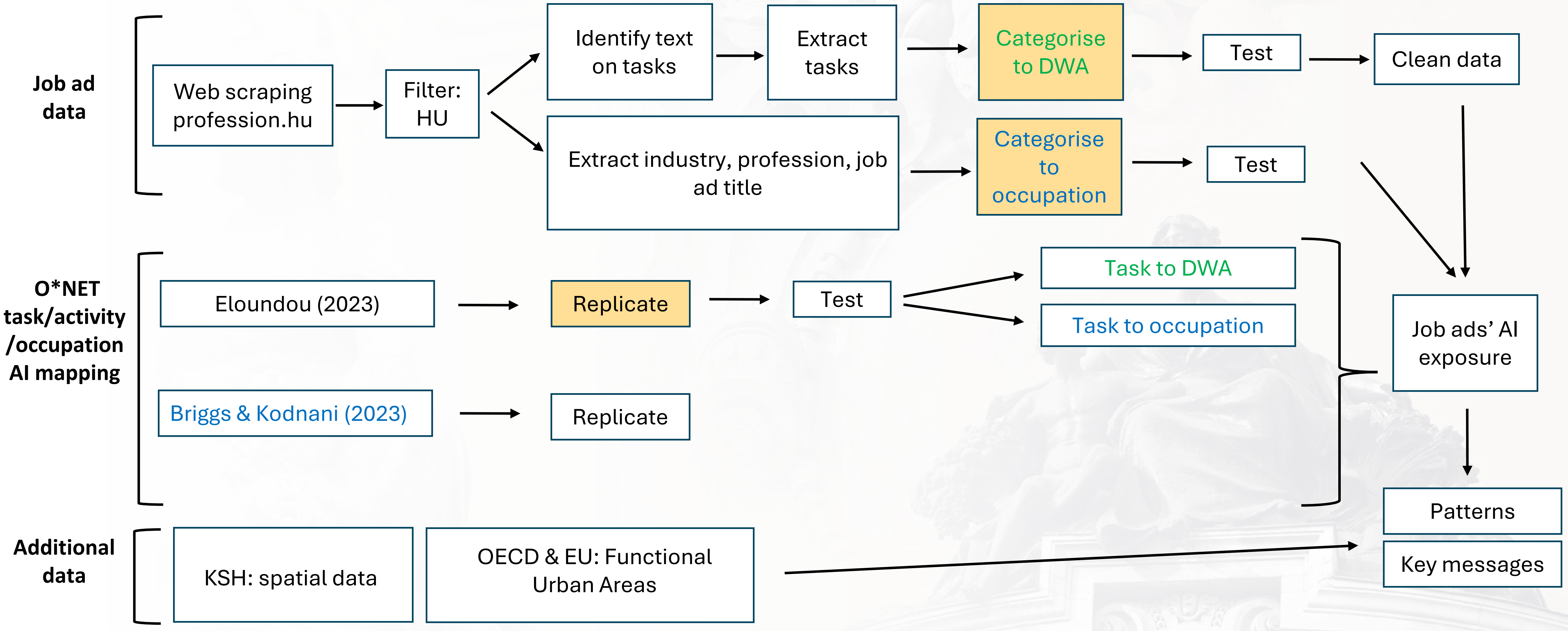
**Novelty and use of our research:**

- Focus on LLMs – much of the literature predates their rapid take-off
- Spatial focus
- Uses detailed job postings data from largest job portal
- Emerging Markets have been less studied

# AI HISTORY OVERVIEW



# RESEARCH PROJECT FLOW CHART




**Key**: DWA, occupation, ChatGPT 4o

# DATA – JOB PORTALS

| Job portal | No of ads (16 Jan 2024) |
| --- | --- |
| **Profession.hu** | **13,850** |
| Linkedin (ads in HU) | 11,045 |
| EURES (ads in HU) | 5,774 |
| CVOnline.hu | 5,703 |
| Jófogás | 2,633 |
| Jobline | 1,561 |
| Jooble (ads in HU) | 12,240 (uses other portals) |

| Job vacancies (2023) | 78,975 |
| --- | --- |

Job portal websites, KSH

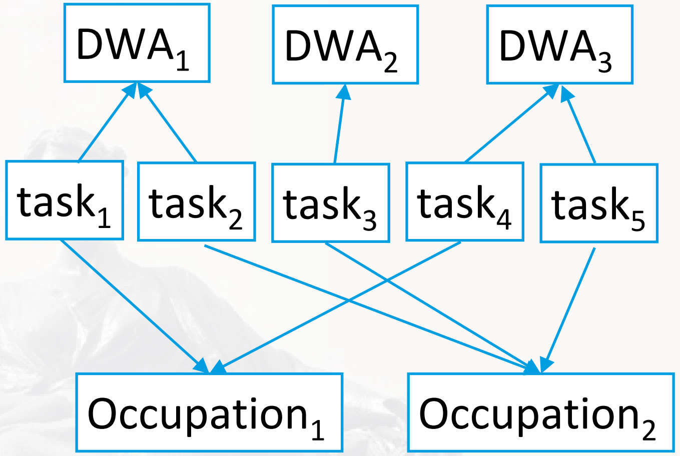
# O*NET DATA

**Detailed Work Activity example:** Classify organisms based on their characteristics or behavior.

c. 2,000

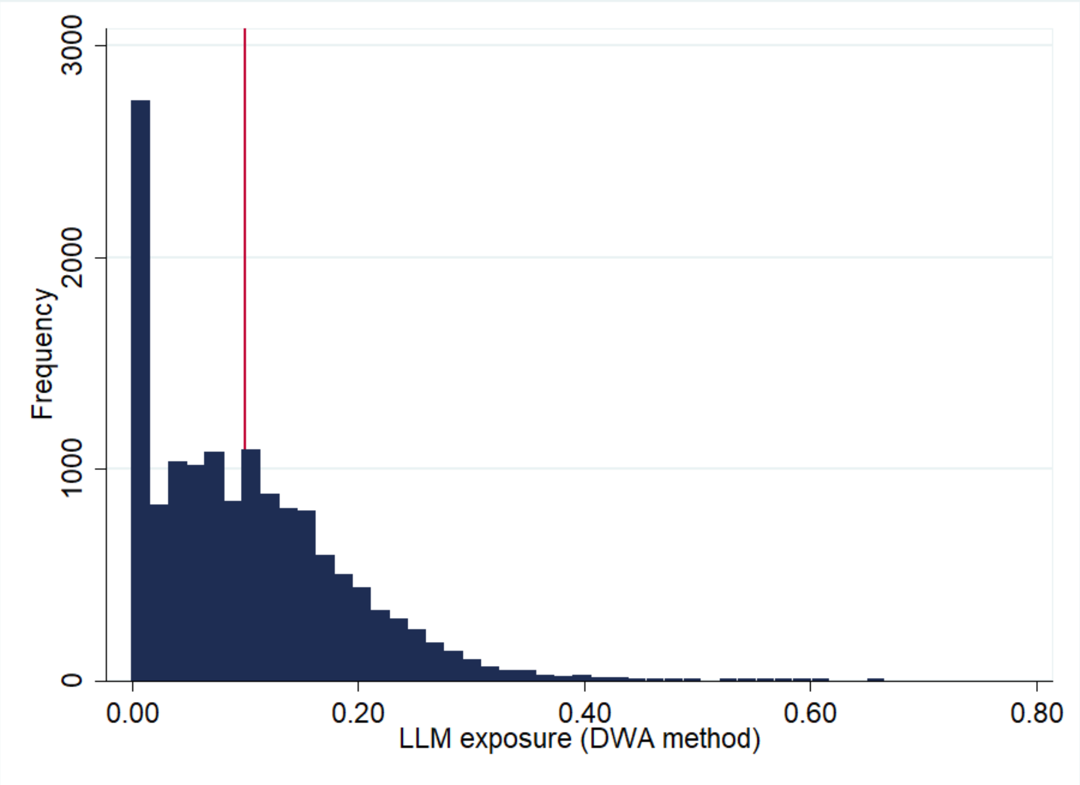
**Task example:** Review, classify, and record survey data in preparation for computer analysis. > 20,000

**Occupation example:** Survey researcher c. 1,000

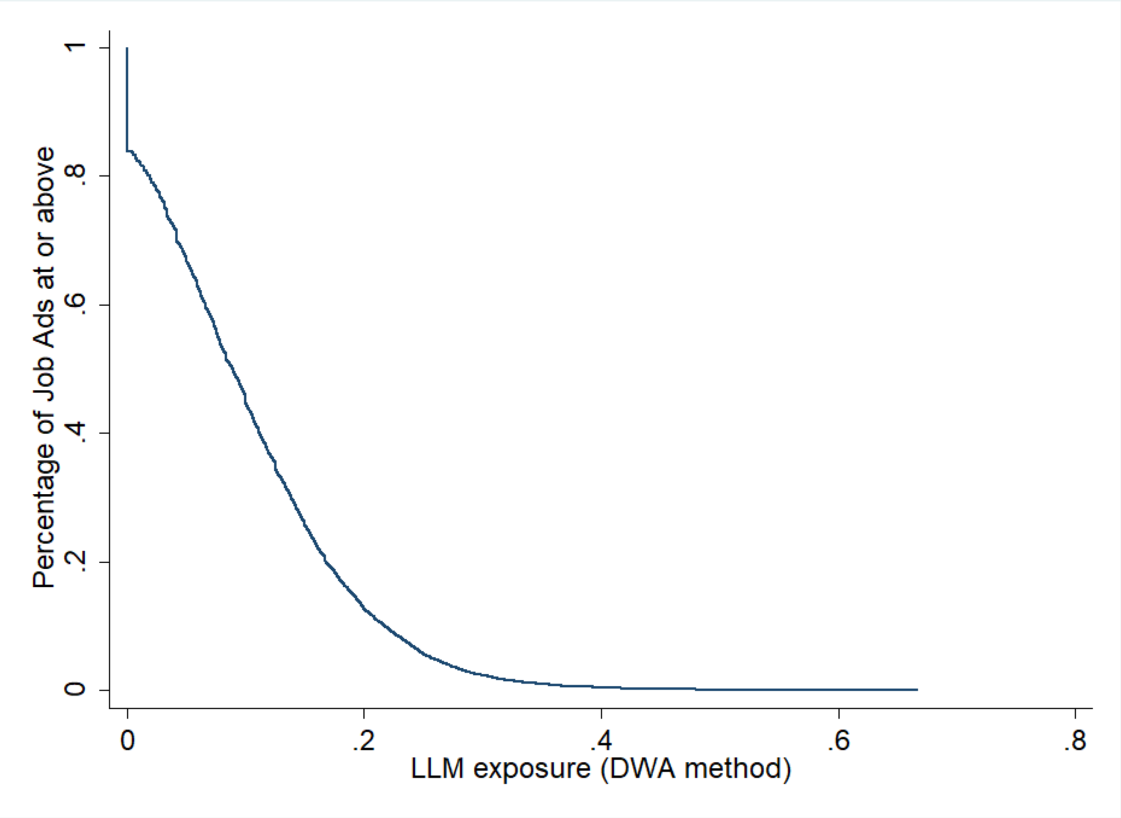


# RESULTS: LLM COMPLEMENTS

Distribution of LLM exposure

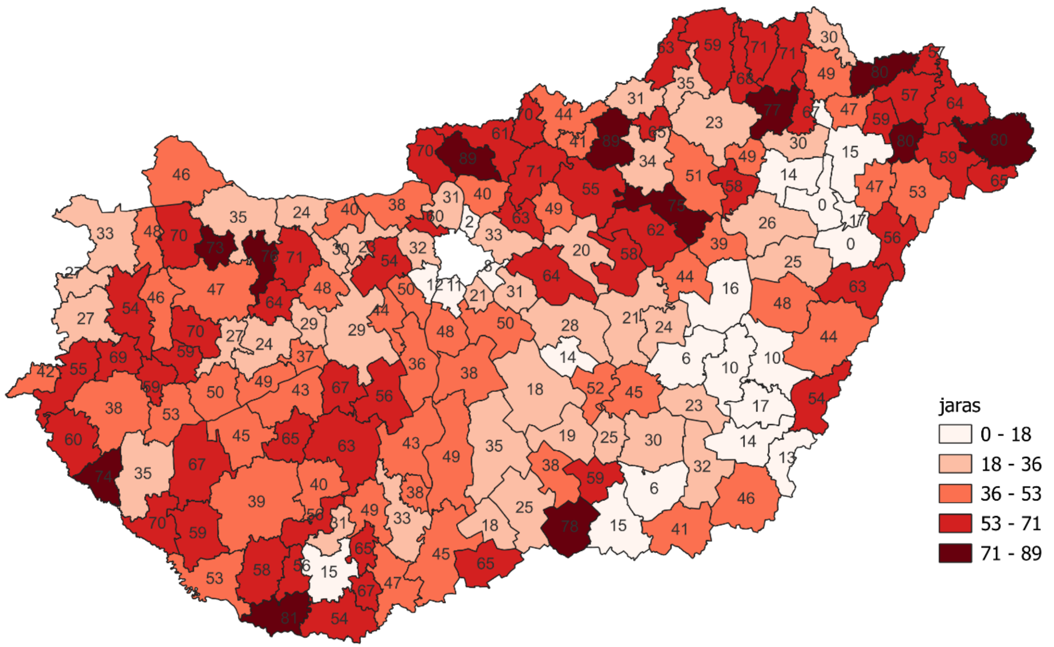



Share of Job ads with LLM exposure> x



# LLM EXPOSURE IS CORRELATED WITH THE TYPE OF SETTLEMENT

## Share of villages by district




Source: KSH

## LLM exposure by type of settlement*


*statistically significant differences at 0.01 level between: i) villages and cities and ii) capital and other cities.

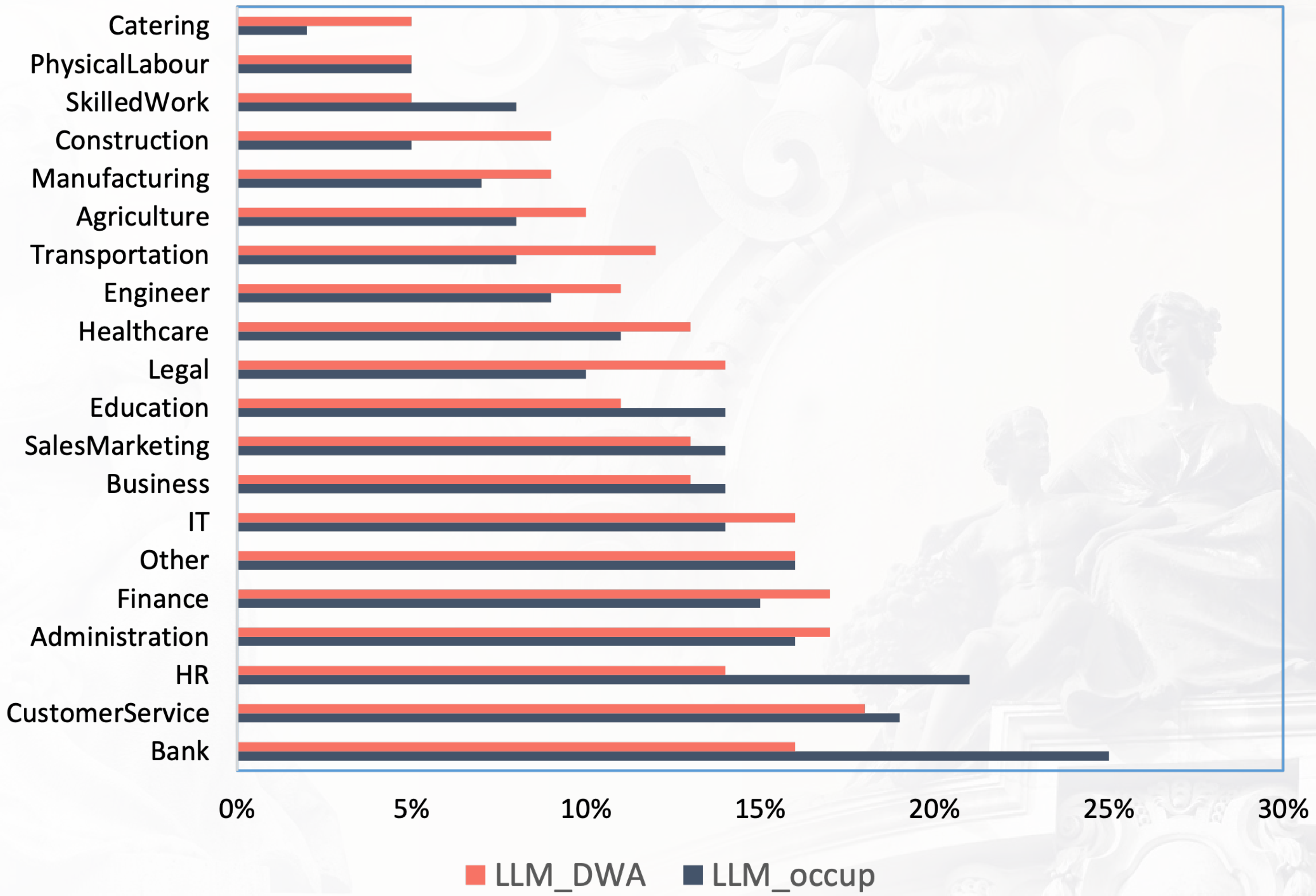
# RESULTS: INDUSTRY MATTERS

**Linear regression with OLS estimation: LMM exposure (DWA method)**

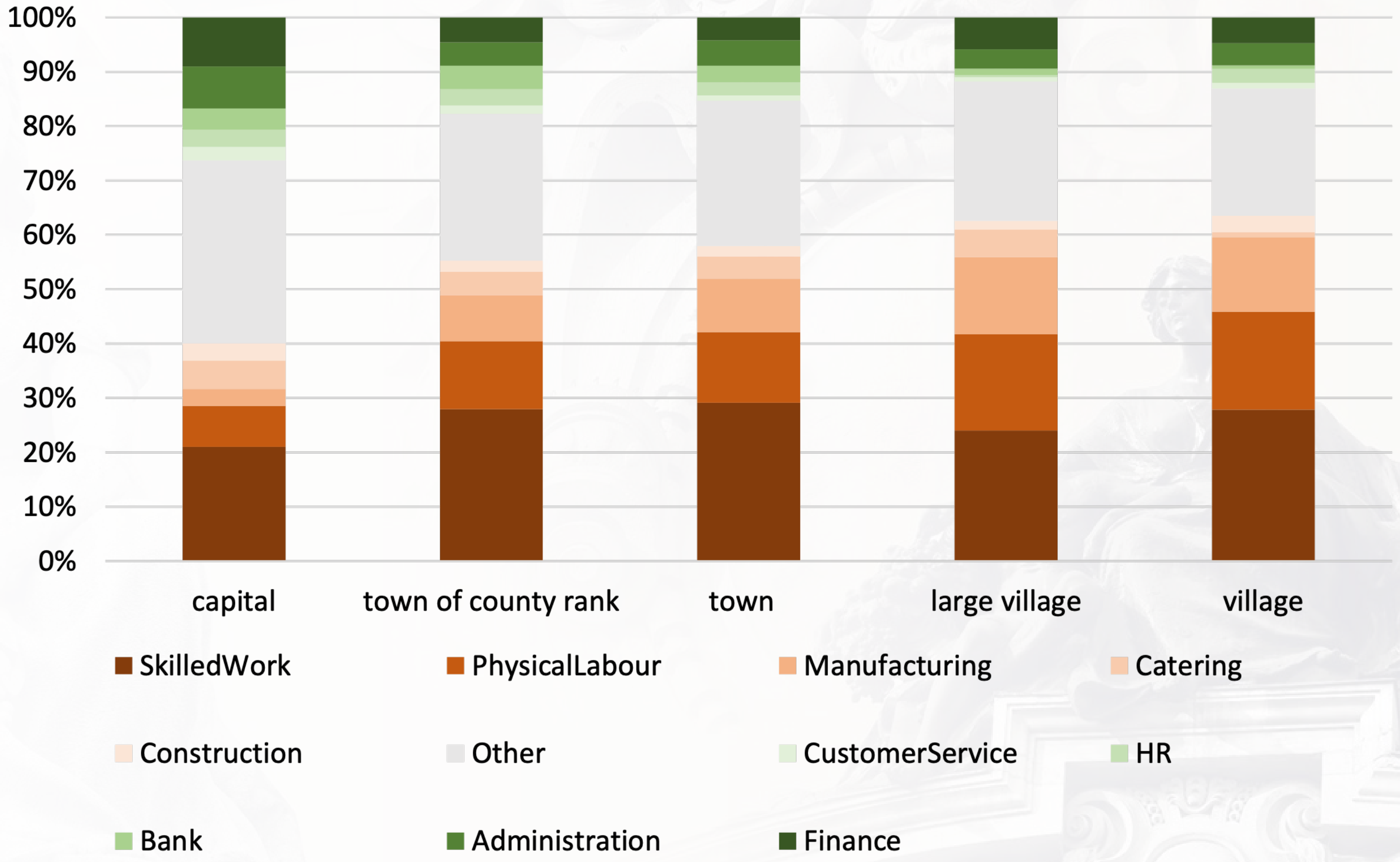
| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Village dummy** | **-0.69**** (0.30) | **-0.73*** (0.38) | -0.33 (0.25) | |
| **Young% (20-30 over 20-60)** | **0.19***** (0.04) | **0.17***** (0.05) | 0.00 (0.03) | |
| **LogEarnings** | **3.94***** (0.47) | -1.18 (1.08) | 0.12 (0.42) | |
| **Constant** | -46.19*** (6.2) | 21.06 (14.11) | 7.56 (5.54) | 9.10*** (1.01) |
| **Industry dummies** | N | N | Y | Y |
| **Budapest FUA excluded?** | N | Y | N | N |
| **Observations** | 13 200 | 4 821 | 13 200 | 13 200 |
| **Prob>F** | 0.00 | 0.00 | 0.00 | 0.00 |
| **R2** | 0.01 | 0.00 | 0.29 | 0.29 |

*Robust standard errors in brackets*

# DIFFERENCES IN EXPOSURE TO LLM ACROSS INDUSTRIES

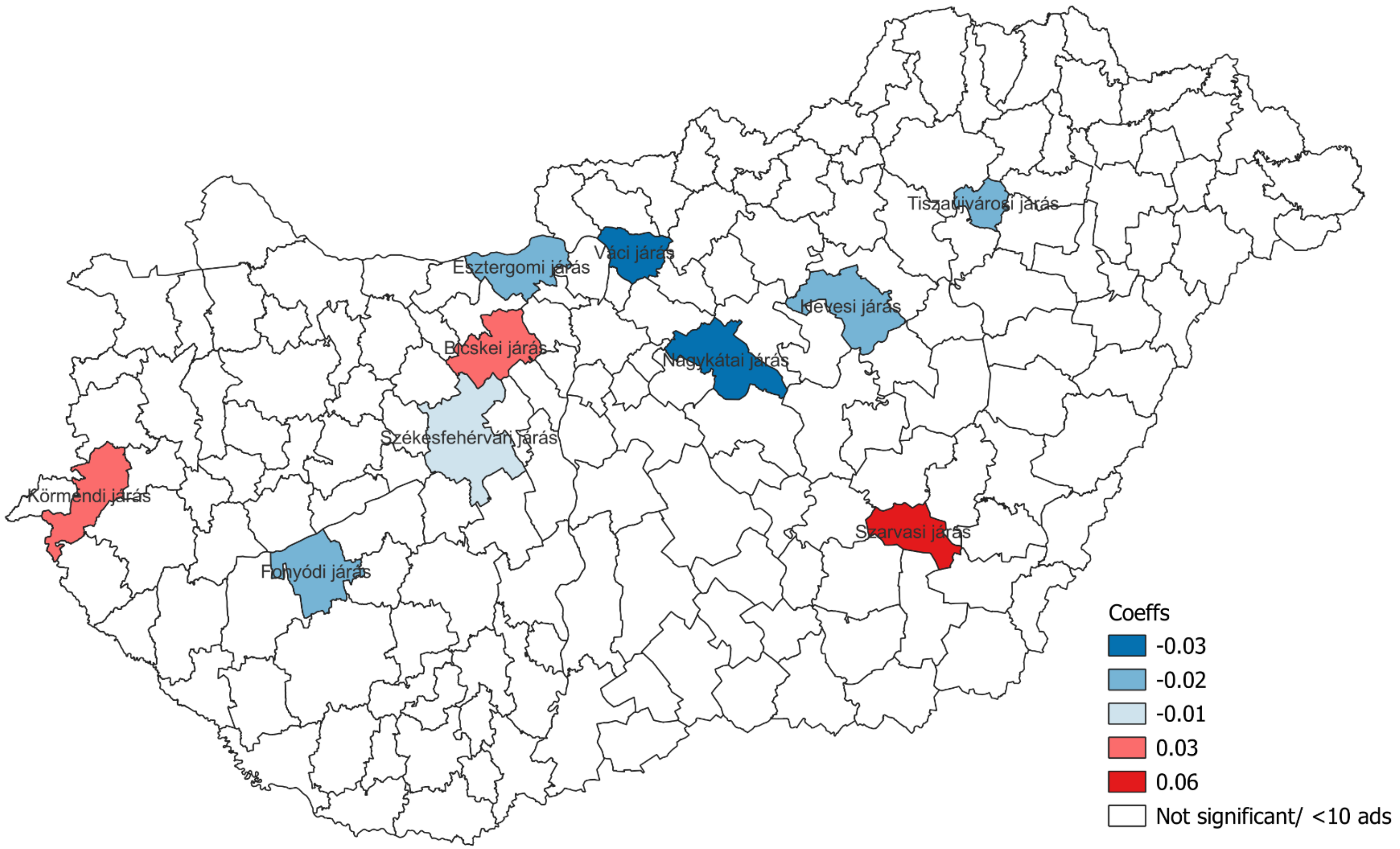


# SETTLEMENT TYPE & INDUSTRY MIX



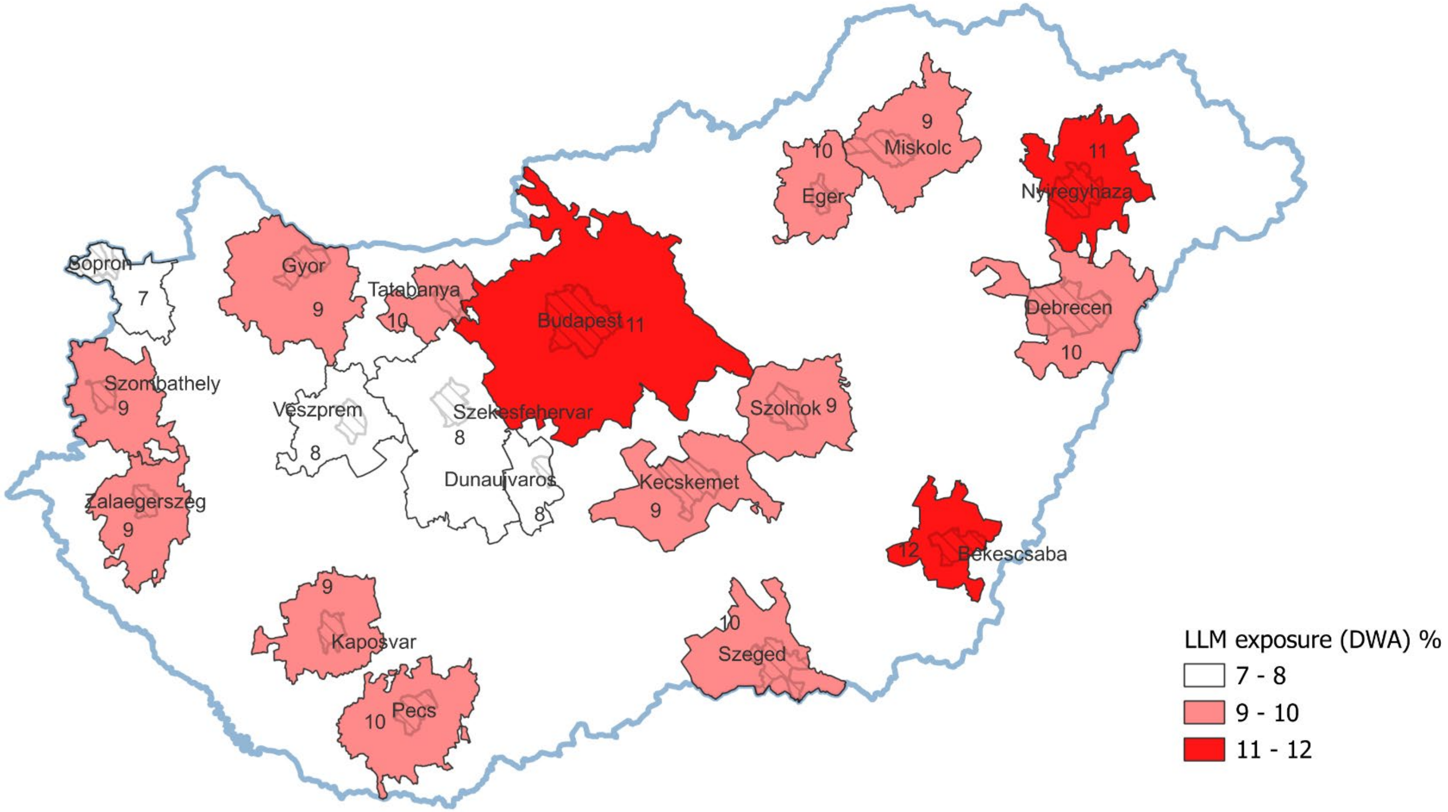
# DIFFERENCES IN EXPOSURE VS INDUSTRY MIX

Where is LLM exposure statistically different from what the district's industry mix would imply?




*Residuals from a regression where y= LLM exposure and x= industries, are then regressed on districts. This map depicts coefficients from the second regression.*

# EXPOSURE BY FUNCTIONAL URBAN AREA




Functional Urban Areas use population density and travel-to-work flows to demarcate areas where labour market is highly integrated. Source: OECD & European Commission and own calculations

- Some cities with a complex industrial profile in the Western part of Hungary close to highways leading to Austria have significant production operations – and higher share of sectors with comparatively low LLM exposure.
- Some cities in the East have comparatively more job offers in more LLM-exposed sectors such as Administration and Banking.

# COMPARISON WITH THE LITERATURE

| Topic | Study | Country | Statement | Our findings |
|---|---|---|---|---|
| Complement vs substitute | Eloundou et al. (2023) Briggs & Kodnani (2023) | US | Rare to find any occupation for which LLMs could do nearly all the work. | Agree. |
| % Exposure | Eloundou et al. (2023) | US | At least 10% (50%) of work tasks affected by LLMs for 80% (20%) of US workforce. | This is true for 45% (0%) of the Hungarian workforce. |
| | Briggs & Kodnani (2023) | World | 18% of work globally could be automated by ***genAI.*** | We also find 18% for ***genAI.*** |
| | Briggs & Kodnani (2023) | US | 2/3 of US occupations are exposed to ***genAI***, most have a 25-50% exposure. | 83% are exposed to ***genAI*** >0.05, 69% exposed>0.1. Almost all between 0-0.4. |
| What/who exposed | Eloundou et al. (2023) | US | Information processing industries exhibit high exposure, while manufacturing, agriculture, and mining demonstrate lower exposure. | Similar. Catering, physical labour and construction also low. |
| Geographical patterns | Hamaguchi (2018) | Japan | Women especially in larger cities more exposed to ***computerization*** (receptionist, clerical work, sales). | Larges cities higher exposure (**LLM**) |
| | Frank (2018) | US | Lower potential for **automation** in big cities rather than small (due to managerial, technical professions) | Larger settlement types more exposed to **LLM**s |
| | Hat (2020) | Austria | urban areas and small towns are relatively less exposed than rural areas to **digitalisation** | Larger settlement types more exposed to **LLM**s |

# LIMITATIONS

- Task/ DWA aggregation to job – mostly simple add-up of tasks, or core/supplementary (no sophisticated weighing)
- Based on current technology (may change soon given rate of development)
- Largely one technology (LLM)
- Looks at technological feasibility, not whether it is economically feasible, doesn't consider security concerns, etc
- Job portal data not representative of jobs available especially rural blue-collar jobs
- Current job ad task descriptions may reflect intention to hire humans. This may change.

# RESULTS

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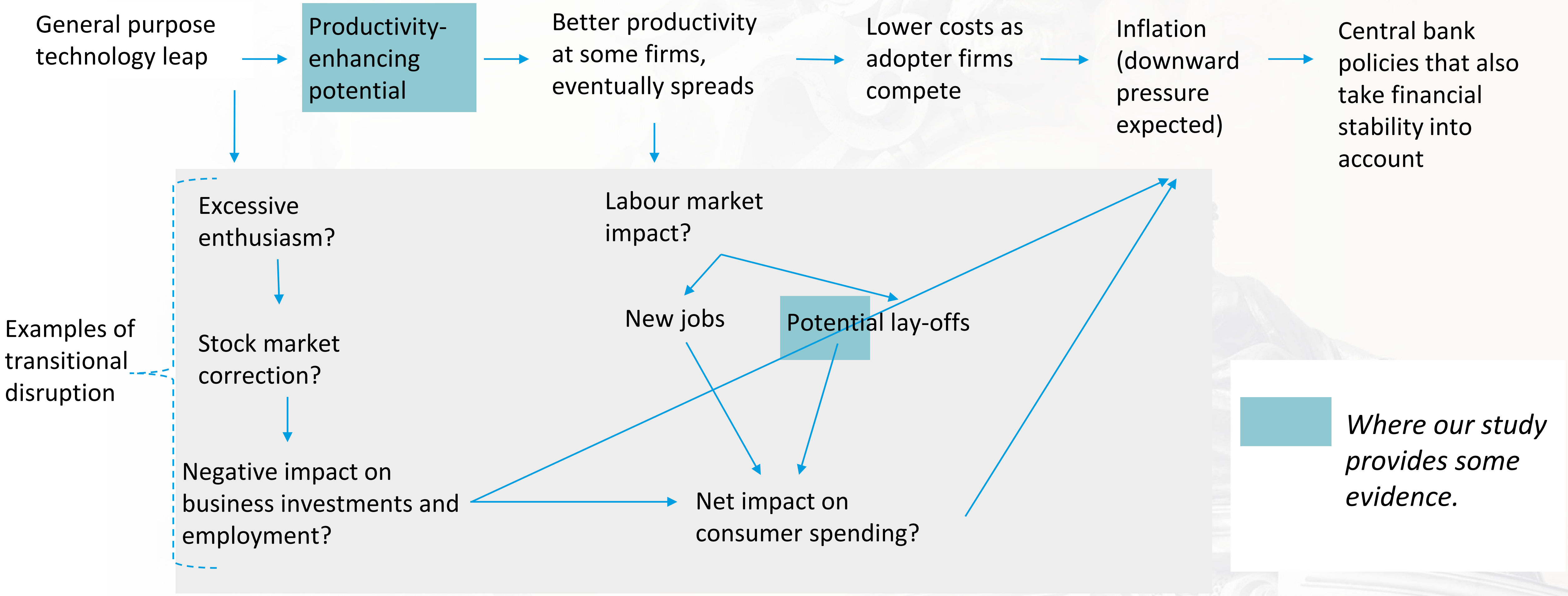
# POSSIBLE IMPLICATIONS

- LLM could be used to improve the productivity of workers.
- Labour market: net effect unclear but LLM complementary to all jobs. Labour market and education policies to ensure benefits are reaped and impact on employment managed.
- Follow-on project: calculate estimate for possible productivity effect -> monetary policy implications.
- Development across many technologies, not just LLM. Nonetheless, do spatial differences in LLM exposure translate to an impact on regional productivity trends (within and across nations)?
- Labour market policies: importance of industries as industry mix is what LLM exposure appears most closely related to.

# TECHNOLOGICAL LEAP AND MONETARY POLICY

## Stylised chart




Based on Poloz (2021) and authors

THANK YOU FOR YOUR ATTENTION!

100 éve Magyarország gyarapodásáért