The Geography of Inventors and Local Knowledge Spillovers in R&D

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[1] Any opinions and conclusions expressed herein are those of the authors and do not represent the views of the U.S. Census Bureau.

Introduction

- Research and Development (R&D) $\Rightarrow$ Aggregate innovation $\Rightarrow$ LR Growth
- R&D concentrates in space. Top 3 West German cities:

Inventors in *Mech. Engineer.*		Workers
29.86% inventors	>	17.39%

- Understudied: causes/consequences of agglomeration economies in R&D

Local Knowledge Spillovers in R&D

Research questions:

1. Evidence on local knowledge spillovers in R&D?
2. Quantitative importance of spillovers when implementing R&D policies?

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Empirics

- Data: Matched administrative panel on German inventors, 1980-2014
  - Inventors' technological clusters and patents' citation counts
- Local Knowledge Spillovers in R&D:
  - Reunification of Germany in 1990 $\Rightarrow$ arrival of East German inventors in West Germany
    - Quasi-exogenous variation across West German clusters
  - $\uparrow 10\%$ cluster size $\Rightarrow \uparrow 4\%$ inventor productivity gains

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Spatial model of innovation

- Tradable intermediate inputs with endogenous quality
  1. Quality determined by firm inventors' R&D
  2. R&D subject to spillovers estimated from the data

R&D policies

1. Inventor mobility matters
   - Complementarity between spillovers and ↓ inventor migration costs
2. R&D subsidies matter
   - Small effect of 25% subsidy from *2020 German R&D Tax Allowance Act*
   - Optimal R&D subsidies are place-based

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Literature

Local knowledge spillovers (Empirical): Griliches (1991); Jaffe et al. (1993); Audretsch and Feldman (1996); Jaffe et al. (2000); Thompson (2006); Carlino et al. (2007); Combes et al. (2010); Greenstone et al. (2010); Bloom et al. (2013); Kerr and Kominers (2015); Kantor and Whalley (2019); Moretti (2021); Gruber et al. (2022)

⇒ Contribution: New evidence on these spillovers

Innovation and knowledge spillovers (Quantitative)

- *Urban:* Eaton and Eckstein (1997); Glaeser (1999); Black and Henderson (1999); Kelly and Hageman (1999); Duranton and Puga (2001); Duranton (2007); Roca and Puga (2017); Duranton and Puga (2019); Davis and Dingel (2019)
- *Trade:* Ramondo et al. (2016); Hallak and Sivadasan (2013); Atkeson and Burstein (2010); Melitz (2003); Eaton and Kortum (2002); Krugman (1980); Akcigit et al. (2021)
- *Spatial:* Desmet and Rossi-Hansberg (2014); Desmet et al. (2018); Nagy et al. (2016); Mestieri et al. (2021)

⇒ Contribution: Migration costs + Spillovers ⇒ Geography of inventors matters in the aggregate

Labor mobility and innovation + productivity + growth

- *Empirical:* Kerr (2010); Borjas and Doran (2012); Burchardi and Hassan (2013); Moser et al. (2014); Peri et al. (2015); Bosetti et al. (2015); Kerr and Kominers (2015); Kerr et al. (2017); Bahar et al. (2020); Burchardi et al. (2020); Bernstein et al. (2022); Chattergoon and Kerr (2022)
- *Quantitative:* Monras (2018); Bryan and Morten (2019); Peters (2019); Arkolakis et al. (2020); Pellegrina and Sotelo (2021); Prato (2021)

⇒ Contribution: Quantification of internal mobility of inventors on productivity

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   $\Rightarrow$ The Reunification of Germany
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Data

Final dataset Inventor/year panel

- *Source:* IAB-FDZ's Linked Inventor Biography (INV-BIO)
- *Agents:* West German inventors, 1980-2014
- *Inventor productivity:* # inventor's new patents' citations
- *Location:* 104 labor markets inventor's establishment
- *Patent type:* 5 technological areas
- *Cluster size:* # inventors in techn. area/labor market pair

Occupation of inventors | Industry of firms | Technological area of patents

Top 10: Electric. engineer. | Top 10: Instruments | Top 10: Chemistry | Top 10: Mechanic. engineer.

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Local Knowledge spillovers in R&D

Baseline specification

$$\log\left(Z^{i\omega}_{da,t}\right) = \iota_{d,t} + \iota_{a,t} + \iota_{da} + \iota_{\omega} + \iota_{i} + \beta \log\left(R_{da,t}\right) + \epsilon^{i\omega}_{da,t}$$

where

- $Z^{i\omega}_{da,t}$: # of inventor i's *new patents'* 5-year forward citations in period t
- $R_{da,t}$: # of inventors in cluster (d,a) in period t

Local Knowledge spillovers in R&D

- Ha: $\beta > 0$

FEs

- $\iota_{d,t}$: amenities + labor market shocks
- $\iota_{a,t}$: technological change
- ι_{da} : cluster-specific productivity
- ι_{ω} : firm-specific productivity
- ι_{i} : sorting from inventor-specific productivity

Baseline Robustness 5-year periods

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Endogeneity concerns

1. Sorting from inventor unobservable shocks
   - Example: inventors selects into a new cluster where less/more productive
   - Downward/upward bias
2. Sorting from cluster unobservable shocks
   - Example: growth expectations for Chemistry in Dusseldorf
   - Upward bias

IV

- Ideal experiment: randomize inventors' location ⇒ regress inventor productivity vs cluster size

- The Reunification of Germany in 1990
  - Arrival of East German inventors across West German clusters
    ⇒ quasi-exogenous variation in cluster size

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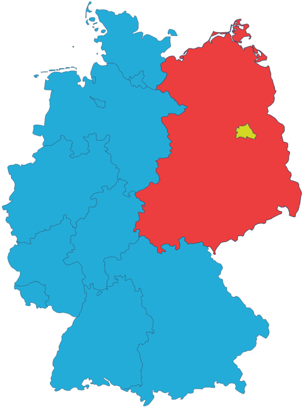
The Reunification of Germany



Background

- 1961: Migration between East and West Germany ceased in 1961
  - 17 years after the German Division
- October 1990: Reunification of Germany begins
  - unexpected and permanent
  - East-West migration, including inventors (Hoisl et al., 2016)

Background: patent system

East-West Exodus

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IV

Model in first differences

$$\Delta \log \left(Z_{da,t}^{i\omega}\right) = \iota_{d,t} + \iota_{a,t} + \beta \Delta \log \left(R_{da,t}\right) + \epsilon_{da,t}^{i\omega}$$

Shift-share instrument

$$IV_{da,t} = \sum_{o \in \mathcal{E}} g_{o,t} \times s_{o,da}$$

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- $g_{o,t} \equiv \log \left(R^{-d,-a}_{o,t} \right)$: # of inventors moved from location $o \in \mathcal{E}$ (in the East) to all West German clusters except to the instrumented cluster (d, a)
- Identification: $\mathbb{E} \left\{ \overline{g\epsilon} \right\} = 0$ (Borusyak et al., 2022)

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$$IV_{da,t} = \sum_{o \in \mathcal{E}} g_{o,t} \times s_{o,da}$$

- $s_{o,da} \equiv dist_{o,d}^{-1} \times TechComp_{o,a}$, where

$\Rightarrow dist_{o,d}^{-1}$: inverse distance between $o \in \mathcal{E}$ and d
$\Rightarrow TechComp_{o,a}$: share of patents of area a in location $o \in \mathcal{E}$

$\uparrow$ CLUSTER SIZE $\Rightarrow$ $\uparrow$ INVENTOR PRODUCTIVITY

	IV			OLS
	(1)	(2)	(3)	(4)
$\Delta \log \left(R_{da,t}\right)$	0.178	0.309	0.409	0.232
	(0.0431)	(0.101)	(0.152)	(0.082)
$\iota_{d,t}$		✓	✓	✓
$\iota_{a,t}$			✓	✓
F stat	132.1	34.14	28.23	.
N	50,778	50,776	50,776	53,145

Robustness
5-year periods
Discussions

Spatial Model of Innovation

1. Model
2. Taking the model to the data
3. R&D policy counterfactuals:
   3.1 $\Downarrow$ Inventor migration costs
   3.2 *2020 German R&D Tax Allowance Act* VS Optimal R&D subsidies

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Model

Geography

- $\mathcal{S} \equiv \{1, 2, \ldots, S\}$ locations $\qquad o, d \in \mathcal{S}$

Technology

- Final goods
  - Non-tradable
  - CES aggregate of intermediate inputs with elast. σ
- Intermediate inputs
  - Tradable
  - Workers produce inputs
- R&D subsidiary
  - Owned by colocated intermediate inputs firm
  - R&D output freely transmitted to intermediate inputs firm
  - Inventors produce R&D $\Rightarrow$ input quality
    - R&D s.t. Local Knowledge Spillovers

Agents

- Workers and inventors
- Inelastic labor supply
- Consume local final good + housing
- Location choice s.t. migration costs

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Intermediate inputs

$$\max_{\{P_{od},Q_{od},L_{od}\}} \pi_o = \sum_d \pi_{od},$$

$$s.t.$$

$$\pi_{od} = P_{od}Q_{od} - w_o^L L_{od},$$

$$L_{od} = \frac{\tau_{od}Q_{od}}{\mathcal{A}_o},$$

$$Q_{od} = Z_o P_{od}^{-\sigma} P_d^{\sigma-1} X_d.$$

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Markup pricing

Demand for intermediates

Quality of intermediate inputs

$$Z_o = \mathbb{Z}_o R_o$$

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- R_o : # of inventors in o

Quality of intermediate inputs

$$Z_o = \mathbb{Z}_o R_o$$

- $\mathbb{Z}_o$: *expected* productivity of inventors' ideas

▶▶ Microfoundation 1: linear improvements

▶▶ Microfoundation 2: necessary tasks

Local Knowledge Spillovers in R&D

Productivity of inventors' ideas

Microfoundation

$$Z_o^i \sim Frechet\left(\alpha, \lambda_o^{\frac{1}{\alpha}}\right)$$

where

- $\lambda_o^{\frac{1}{\alpha}} = \mathcal{Z}_o R_o^{\widetilde{\gamma}}$, where $R_o^{\widetilde{\gamma}}$ and $\widetilde{\gamma} \equiv \frac{\gamma}{\alpha}$ are Local Knowledge Spillovers in R&D

Expected productivity of inventors' ideas

$$\mathbb{Z}_o = \mathbb{E}\left\{Z_o^i\right\} = \psi \lambda_o^{\frac{1}{\alpha}} = \psi \mathcal{Z}_o R_o^{\widetilde{\gamma}}$$

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R&D

- R&D subsidiary maximizes R&D output:

$$\max_{\{R_o\}} Z_o - w_o^R R_o$$
$$s.t.$$
$$Z_o = \psi \mathcal{Z}_o R_o^{1+\widetilde{\gamma}}$$

- Demand for inventors

$$w_o^R = \psi \mathcal{Z}_o R_o^{\widetilde{\gamma}}$$

Location choice

- Agent i of type $n = \{L, R\}$ working in o moves to d:

$$U_{od}^{i,n} = \max_{d \in \mathcal{S}} \left\{ \frac{U_d^n}{\mu_{od}^n} \times \epsilon^i \right\},$$

  where
  - $U_d^n = \frac{\mathcal{B}_d^n V_d^n}{P_d^{\beta} r_d^{1-\beta}}$: indirect utility
  - $V_d^n = \frac{(1+\overline{\pi}) w_d^n}{\beta}$: income
  - $\mathcal{B}_d^n$: type-specific location amenities
  - $\epsilon^i \overset{iid}{\sim} G(\epsilon) = \exp\left(-\epsilon^{-\kappa}\right)$
  - μ_{od}^n : iceberg migration costs

Details

- Migration shares:

$$\eta_{od}^n = \frac{\left(\frac{U_d^n}{\mu_{od}^n}\right)^{\kappa}}{\sum_{\delta}\left(\frac{U_{\delta}^n}{\mu_{o\delta}^L}\right)^{\kappa}} \quad , n = \{L, R\}$$

Equilibrium

Given the exogenous distribution of workers and inventors across locations $\{\overline{R}_o, \overline{L}_o\}_{\forall o \in \mathcal{S}}$, fixed supply of housing $\{\overline{H}_o\}_{\forall o \in \mathcal{S}}$, location fundamentals $\{\mathcal{Z}_o, \mathcal{A}_o\}_{\forall o \in \mathcal{S}}$, location amenities $\{\mathcal{B}^R_o, \mathcal{B}^L_o\}_{\forall o \in \mathcal{S}}$, migration costs $\{\mu^R_{od}, \mu^L_{od}\}_{\forall o,d \in \mathcal{S},\mathcal{S}}$, trade costs $\{\tau_{od}\}_{\forall o,d \in \mathcal{S},\mathcal{S}}$, and parameters, *an equilibrium is a set of wages* $\{w^R_o, w^L_o\}_{\forall o \in \mathcal{S}}$, *housing rent* $\{r_o\}_{\forall o \in \mathcal{S}}$, *prices* $\{P_o\}_{\forall o \in \mathcal{S}}$, *quantities* $\{R_o, L_o, H_o, Q_o\}_{\forall o \in \mathcal{S}}$, *and quality* $\{Z_o\}_{\forall o \in \mathcal{S}}$ *such that*

1. *workers and inventors maximize utility*
2. *firms maximize profits*
3. *workers and inventors labor markets clear* Details
4. *housing market clears* Details
5. *trade is balanced* Details

Equilibrium with RD subsidies

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Taking the model to the data

- Local Knowledge Spillovers in R&D ($\widetilde{\gamma}$)
- Migration costs $\{\mu_{od}^{n}\}^{n=\{L,R\}}$ ⏩ Details
- Trade costs $\{\tau_{od}\}$ ⏩ Details
- Location fundamentals $\{\mathcal{A}_o, \mathcal{Z}_o\}$ ⏩ Details
- Location amenities $\{\mathcal{B}_o^n\}^{n=\{L,R\}}$ ⏩ Details

Local Knowledge Spillovers in R&D ($\widetilde{\gamma}$)

- From properties of the Frechet distribution:

$$\log\left(Z_o^i\right) = \widetilde{\gamma}\log\left(R_o\right) + \epsilon_o^i$$

- Reduced-form evidence:

$$\Delta\log\left(Z_{oa,t}^{i\omega}\right) = FEs + \underbrace{\beta}_{0.409}\Delta\log\left(R_{oa,t}\right) + \Delta\epsilon_{oa,t}^{i\omega}$$

- Lanjouw and Schankerman (2004): Elasticity of patent quality to 5-year forward citations $= 0.22$
$\Rightarrow \widetilde{\gamma} = (0.22)\,\beta \approx 0.09$ VS $\widetilde{\gamma} = 0.07$ (Moretti, 2021)

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Spatial Model of Innovation

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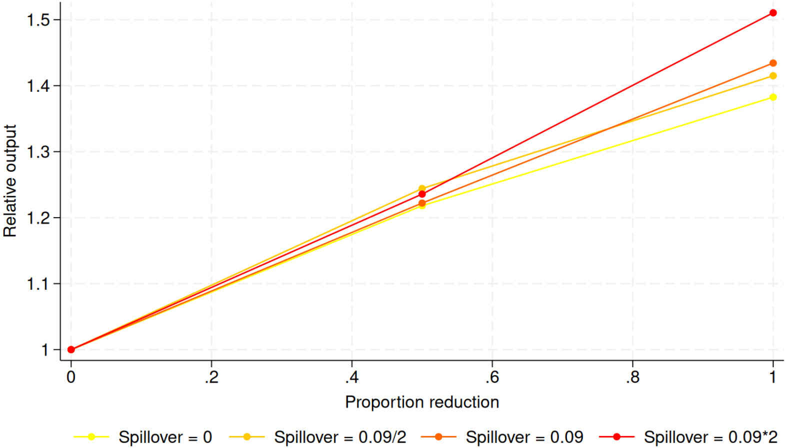
2. Taking the model to the data
3. R&D policy counterfactuals:
    3.1 $\Downarrow$ Inventor migration costs
    3.2 *2020 German R&D Tax Allowance Act* VS Optimal R&D subsidies

⇓ Inventor migration costs

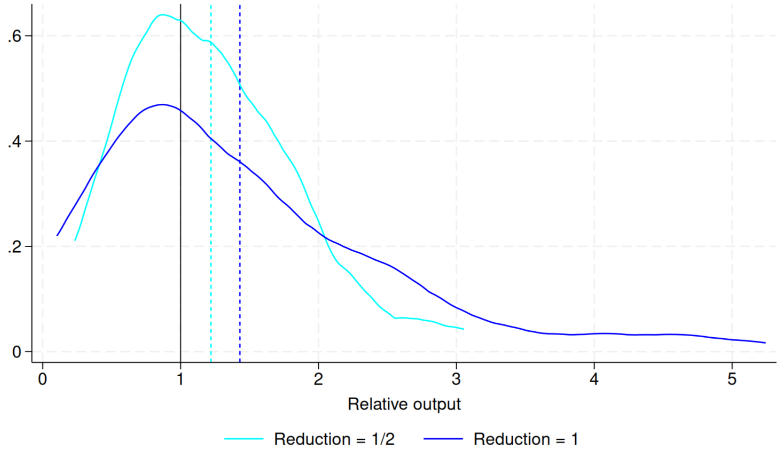
Reducing migration costs for inventors is key to promote economic activity



- X-axis: $\widehat{\mu^R_{od}} = \mu_{od}^{R^{(1-\kappa)}}$
- Y-axis: $\mathbb{E}\left\{\frac{\widehat{Q_d}}{Q_d}\right\}^{\widetilde{\gamma}=\gamma^*}$

$\Downarrow$ Inventor migration costs

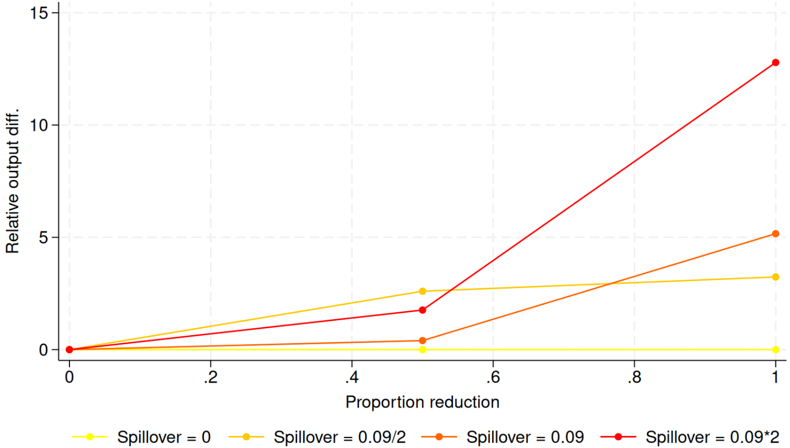
Large heterogeneous effects



- X-axis: $\frac{\widehat{Q_d}}{Q_d}$
- Given $\widetilde{\gamma} = 0.09$

$\Downarrow$ Inventor migration costs

Complementarity between spillovers and reduction in inventor migration costs



- X-axis: $\widehat{\mu^R_{od}} = \mu^{R^{(1-\kappa)}}_{od}$
- Y-axis: $\mathbb{E}\left\{\frac{\widehat{Q_d}}{Q_d}\right\}^{\widetilde{\gamma}=\gamma^*} - \mathbb{E}\left\{\frac{\widehat{Q_d}}{Q_d}\right\}^{\widetilde{\gamma}=0}$

Spatial Model of Innovation

1. Model
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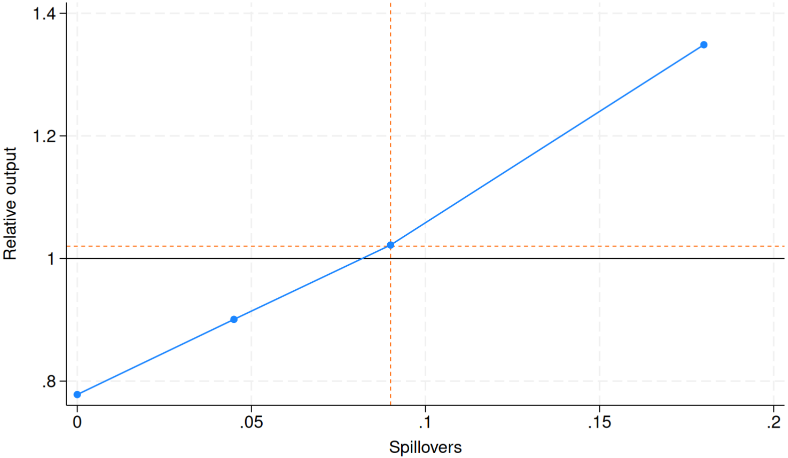
3. R&D policy counterfactuals:
   3.1 $\Downarrow$ Inventor migration costs
   3.2 *2020 German R&D Tax Allowance Act* VS Optimal R&D subsidies

2020 German R&D Tax Allowance Act

- 2020 German R&D Tax Allowance Act
  - 25% subsidy to all R&D expenditures
  - blind to geography

2020 German R&D Tax Allowance Act

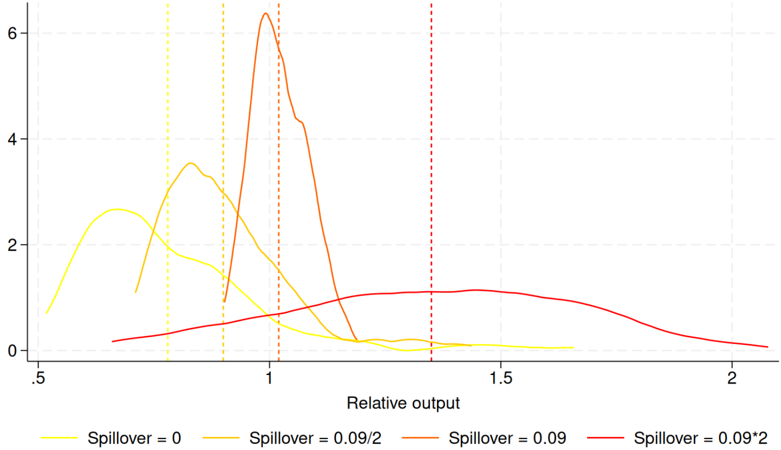
The 2020 R&D Act would increase output by 2.2% on average



- X-axis: γ
- Y-axis: $\mathbb{E}\left\{\frac{\widehat{Q_d}}{Q_d}\right\}^{\gamma=\widetilde{\gamma}}$

2020 German R&D Tax Allowance Act

Large heterogeneous effects



- X-axis: $\left\{\frac{\widehat{Q_d}}{Q_d}\right\}^{\widetilde{\gamma}}$

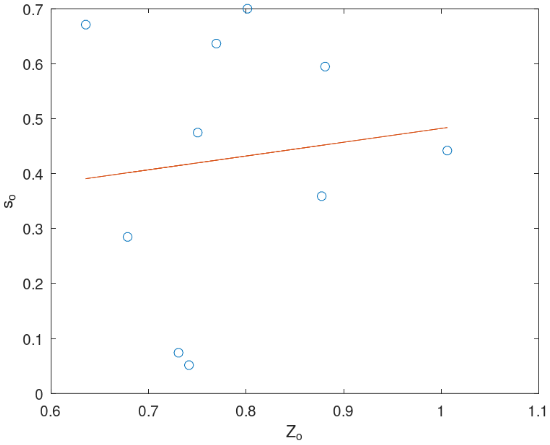
Optimal R&D subsidies

- Economy is inefficient due to spillovers $\Rightarrow$ **Which R&D subsidies would make the economy efficient?**

1. Solve the planner problem ⏩ Details
2. Back out set of R&D subsidies $\{s_o^*\}$ such that Competitive Equilibrium with R&D subsidies $\iff$ Planner Equilibrium
3. Compare $\{s_o^*\}$ with the 2020 German R&D Tax Allowance Act

Optimal R&D subsidies

Place-based R&D policies: larger subsidies to locations with better fundamentals for R&D



- X-axis: $\mathcal{Z}_o$
- Y-axis: s_o^*

Conclusions

- Causal estimation of Local Knowledge Spillovers in R&D: Reunification of Germany in 1990
- Built a spatial model of innovation
  - The geography of inventors matters in the aggregate
- Implementing R&D policies in explicit geography
  - Since inventors are few, of interest to policy-makers to increase output
  - Spillovers crucial when implementing R&D policies

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Distribution of inventors, by occupation

Occupation	Share
Technical research and development, construction, and production planning and scheduling	19.23%
Machine-building and automotive industry	19.10%
Mechatronics, energy electronics and electrical engineering	15.77%
Mathematics, biology, chemistry and physics	15.74%
Business management and organization	10.36%
Others	19.8%

Back to data

Distribution of establishments, by industry

Industry	Share
Manufacturing, mining and quarrying and other industry	38.59%
Wholesale and retail trade, transportation and storage, accommodation and food service activities	18.76%
Real estate activities	12.90%
Professional, scientific, technical, administration and support service activities	7.87%
Financial and insurance activities	5.56%
Construction	5.31%
Agriculture, forestry and fishing	4.84%
Information and communication	3.15%
Public administration, defence, education, human health and social work activities	2.29%
Other services	0.68%

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Distrution of patents, by technological class

Technological area	Share
Mechanical engineering	38.39%
Chemistry	25%
Electrical engineering	18.09%
Instruments	12.64%
Other fields	5.85%

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Top 10 cities: Electrical engineering

Code	*City*	*Share*
59	Stuttgart	15.0968
80	Munchen	13.7764
90	Regensburg	5.9419
97	Nurnberg	4.5334
96	Erlangen	4.0492
65	Karlsruhe	4.0052
60	Boblingen	2.7728
74	Reutlingen	2.7288
41	Soest	2.5528
43	Frankfurt am Main	2.2007

Back to data

Top 10 cities: Instruments

Code	*City*	*Share*
59	Stuttgart	13.5844
80	Munchen	8.7328
64	Heidenheim	6.5068
96	Erlangen	5.7648
60	Boblingen	4.9657
43	Frankfurt am Main	4.1095
70	Rottweil	4.0525
68	Freiburg	3.4246
90	Regensburg	2.9680
65	Karlsruhe	2.8538

Back to data

Top 10 cities: Chemistry

Code	*City*	*Share*
24	Dusseldorf	11.0110
59	Stuttgart	10.7340
5	Hamburg	7.2022
80	Munchen	6.3019
43	Frankfurt am Main	5.6094
81	Altotting	2.9085
25	Essen	2.7008
29	Koln	2.4238
74	Reutlingen	2.4238
96	Erlangen	2.2853

Back to data

Top 10 cities: Mechanical engineering

Code	*City*	*Share*
59	Stuttgart	15.8658
80	Munchen	8.1403
60	Boblingen	5.8589
43	Frankfurt am Main	3.5776
77	Ravensburg	3.3183
96	Erlangen	3.1973
65	Karlsruhe	3.0936
7	Wolsfburg	2.5924
24	Dusseldorf	2.5406
62	Heilbronn	2.4714

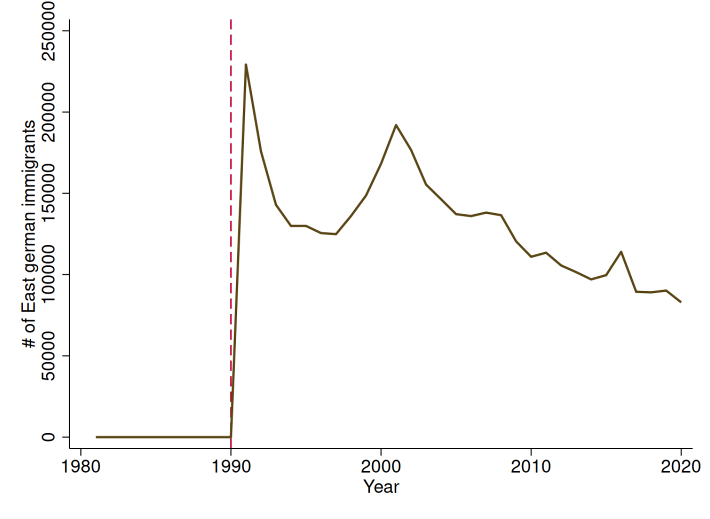
Back to data

German Patent System

- Patent systems in Germany:
  - West Germany: German Patent Office (DPA)
  - East Germany: Office of Inventions and Patents (AfEP)
- Legal frameworks almost identical before reunification
- Merged after reunification
  - Integration of 13.5 million patent documents

Back to the Reunification

The Exodus to the West



Back to the Reunification

OLS models, baseline specification

	(1)	(2)	(3)	(4)	(5)	(6)
$\log(R_{da,t})$	0.0705	0.111	0.0985	0.109	0.0896	0.175
	(0.0256)	(0.0170)	(0.0166)	(0.0385)	(0.0358)	(0.0660)
$\iota_{d,t}$		✓	✓	✓	✓	✓
$\iota_{a,t}$			✓	✓	✓	✓
ι_{da}				✓	✓	✓
ι_{ω}					✓	✓
ι_{i}						✓
N	177,301	177,300	177,300	177,294	162,803	84,639
R^2	0.008	0.053	0.064	0.079	0.246	0.700

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OLS MODELS, ROBUSTNESS

	Panel A: $\log(1+Z)$					
	(1)	(2)	(3)	(4)	(5)	(6)
EPO	0.117	0.143	0.224	0.184	0.0859	0.173
	(0.0186)	(0.0173)	(0.0135)	(0.0319)	(0.0349)	(0.0679)
EU	0.142	0.193	0.255	0.203	0.103	0.245
	(0.0208)	(0.0162)	(0.0178)	(0.0461)	(0.0463)	(0.0864)
$\iota_{d,t}$		✓	✓	✓	✓	✓
$\iota_{a,t}$			✓	✓	✓	✓
ι_{da}				✓	✓	✓
ι_{ω}					✓	✓
ι_{i}						✓
N	177,301	177,300	177,300	177,294	162,803	84,639

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OLS MODELS, ROBUSTNESS

	Panel B: IHS (Z)					
	(1)	(2)	(3)	(4)	(5)	(6)
DPMA	0.0847	0.135	0.118	0.130	0.108	0.217
	(0.0326)	(0.0209)	(0.0205)	(0.0475)	(0.0440)	(0.0798)
EPO	0.140	0.171	0.266	0.223	0.102	0.214
	(0.0219)	(0.0204)	(0.0160)	(0.0389)	(0.0431)	(0.0810)
EU	0.142	0.193	0.255	0.203	0.103	0.245
	(0.0208)	(0.0162)	(0.0178)	(0.0461)	(0.0463)	(0.0864)
$\iota_{d,t}$		✓	✓	✓	✓	✓
$\iota_{a,t}$			✓	✓	✓	✓
ι_{da}				✓	✓	✓
ι_{ω}					✓	✓
ι_{i}						✓
N	177,301	177,300	177,300	177,294	162,803	84,639

Back

OLS models, 5-year periods

	(1)	(2)	(3)	(4)	(5)	(6)
$\log(1+Z)$	0.0291	0.0472	0.0449	0.0707	0.0664	0.0907
	(0.0096)	(0.007)	(0.0073)	(0.0146)	(0.0135)	(0.0215)
$IHS(Z)$	0.0368	0.060	0.0568	0.0902	0.0850	0.116
	(0.0124)	(0.0089)	(0.0094)	(0.0187)	(0.0171)	(0.0273)
$\iota_{d,t}$		✓	✓	✓	✓	✓
$\iota_{a,t}$			✓	✓	✓	✓
ι_{da}				✓	✓	✓
ι_{ω}					✓	✓
ι_{i}						✓
N	177,301	177,300	177,300	177,294	162,803	84,639

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IV models, robustness

	Panel A: $\Delta \log(1+Z)$		
	(1)	(2)	(3)
EPO	0.164	0.139	0.209
	(0.0422)	(0.0723)	(0.117)
EU	0.210	0.270	0.343
	(0.0436)	(0.0907)	(0.143)
$\iota_{d,t}$		✓	✓
$\iota_{a,t}$			✓
$KP-F$	132.1	34.14	28.23
N	50,778	50,776	50,776

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IV MODELS, ROBUSTNESS

	Panel B: $\Delta IHS\,(Z)$		
	(1)	(2)	(3)
DPMA	0.215	0.380	0.498
	(0.0514)	(0.122)	(0.184)
EPO	0.182	0.144	0.237
	(0.0494)	(0.0849)	(0.140)
EU	0.235	0.304	0.393
	(0.0588)	(0.104)	(0.168)
$\iota_{d,t}$		✓	✓
$\iota_{a,t}$			✓
$KP-F$	132.1	34.14	28.23
N	50,778	50,776	50,776

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IV models, 5-year periods

	(1)	(2)	(3)
$\Delta \log(1+Z)$	0.0367	0.0865	0.0849
	(0.0232)	(0.0331)	(0.0428)
$\Delta IHS(Z)$	0.0464	0.109	0.104
	(0.0295)	(0.0420)	(0.0543)
$\iota_{d,t}$		✓	✓
$\iota_{a,t}$			✓
$KP-F$	85.96	26.64	38.15
N	100,234	100,228	100,228

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Discussions

1. Do citations measure productivity?
2. Exposure instead of knowledge spillovers?
3. Comparison to previous estimates

Do citations measure productivity?

- Positive relationship between number of citations and proxies for productivity, such as patent value (Kogan et al., 2017; Hall et al., 2001; Harhoff et al., 1999; Trajtenberg, 1990)
- More recently, preliminary evidence of a inverse U-shaped relationship between number of citations and patent value in the data Abrams et al. (2013)
  - Productive vs strategic patents
  - Are German patents mostly productive or strategic?
- Literature on firm surveys about their incentives to patent (Blind et al., 2006; Cohen et al., 2002; Pitkethly, 2001; Duguet and Kabla, 2000; Schalk et al., 1999; Arundel et al., 1995)
  - Main motive of German firms to file patents: protection of ideas $\Rightarrow$ productive $\Rightarrow$ positive relationship

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Exposure instead of knowledge spillovers?

- Identification threat: # citations reflect higher exposure of an inventor's ideas
  - upward bias
- 2 arguments against this concern:
  1. Germany reports one of the largest number of patent litigation cases (Cremers et al., 2017), and exhibits one of the highest cross-country levels of patent enforcement (Papageorgiadis and Sofka, 2020).
  2. Estimations based on EPO citations

Back

Comparison to previous estimates

- Carlino et al. (2007): $\uparrow$ 10% population $\Rightarrow$ $\uparrow$ 1.95% rate of patenting per-capita across US MAs
    1. Inventor productivity VS US MAs patenting rates
    2. Knowledge spillovers in R&D VS Overall knowledge spillovers
    3. Identification from natural experiment VS Controls
- Moretti (2021): $\uparrow$ 10% cluster size $\Rightarrow$ $\uparrow$ 0.5% inventor productivity
    1. Long-run vs short-run elasticities
    2. Germany vs US

Back

Microfoundation: Generation of ideas

- Innovation *a la* Kortum (1997)
- Consider inventor i living in o
- Steps:
  1. Inventor i draws idea $j \in [1, T_o]$ with productivity Z^{ij}
  2. Selects the best idea, so $Z_o^i = \max_{j=1,\ldots,T_o} Z^{ij}$
  3. If $T_o \sim \mathit{Poisson}\,(\lambda_o)$ and $Z^{ij} \sim \mathit{Pareto}\,(\alpha)$

     $\Rightarrow Z_o^i \sim \mathit{Frechet}\left(\alpha, \lambda_o^{\frac{1}{\alpha}}\right),$

     where λ_o is the *spillover function*

Back to knowledge spillovers

Microfoundation I: linear improvement

- Steps:
  1. Inventors R_o show up to work and line up
  2. first in line receives blueprint, improves it, passes it over
- Endogenous quality:

$$Z_o = \mathbb{Z}_o R_o,$$

where $\mathbb{Z}_o^{\omega} \equiv \mathbb{E}\left\{Z_o^{i\omega}\right\} = \Gamma\left(1 - \frac{1}{\alpha}\right)\lambda_o^{\frac{1}{\alpha}}$, where $\Gamma(\cdot)$ is the Gamma function

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Microfoundation II: necessary tasks

- Steps:
  1. A blueprint is continuum of *necessary* tasks $\mathcal{T} \equiv [0, 1]$
  2. Aggregate quality improvements

$$Z_o = \exp\left(\int_{\mathcal{T}} \log\left(Z_o\left(t\right)\right) dt\right)$$

  3. Quality of task $t \in \mathcal{T}$

$$Z_o\left(t\right) = Z\left(t\right) R_o,$$

     where $Z\left(t\right)$ is drawn from Z_o^i
  4. Rewrite quality as

$$Z_o = \exp\left(\frac{\overline{\gamma}}{\alpha}\right) \lambda_o^{\frac{1}{\alpha}} R_o,$$

     where $\overline{\gamma}$ is Euler's constant

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Demand of intermediates

- Final good: CES aggregator of intermediates

$$Q_d = \left(\sum_o Z_o^{\frac{1}{\sigma}} Q_{od}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

- Demand for intermediates:

$$Q_{od} = Z_o P_{od}^{-\sigma} P_d^{\sigma-1} X_d,$$

where $X_d \equiv P_d Q_d$, and $P_d^{1-\sigma} = \sum_o Z_o P_{od}^{1-\sigma}$.

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Firm optimization

- Firms maximize profits:

$$\max_{\{P_{od}, Q_{od}, L_{od}\}} \pi_o = \sum_d \pi_{od},$$
$$s.t.$$
$$\begin{aligned} \pi_{od} &= P_{od} Q_{od} - w_o^L L_{od}, \\ L_{od} &= \frac{\tau_{od} Q_{od}}{\mathcal{A}_o}, \\ Q_{od} &= Z_o P_{od}^{-\sigma} P_d^{\sigma-1} X_d. \end{aligned}$$

- FOCs wrt $\{P_{od}, Q_{od}, L_{od}\}$ yields markup pricing:

$$P_{od} = \overline{m} \frac{\tau_{od} w_o^L}{\mathcal{A}_o}$$

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Demand of final goods

- Preferences of agents of workers ($n = L$) and inventors ($n = R$)
- Preferences local final good (q_d^n) + housing (h_d^n) + location amenities ($\mathcal{B}_d^n$):

$$\max_{\{q_d^n, h_d^n\}} U_d = \mathcal{B}_d^n \left(\frac{q_d^n}{\beta}\right)^{\beta} \left(\frac{h_d^n}{1-\beta}\right)^{1-\beta}$$

$$s.t. P_d q_d^n + r_d h_d^n = V_d^n,$$

  where V_d^n is the agent's income, and β is the expenditure share on local final goods.

- Indirect utility:

$$U_d^n = \frac{\mathcal{B}_d^n V_d^n}{P_d^{\beta} r_d^{1-\beta}}$$

- Income:

$$V_d^n = (1 + \overline{\pi}) w_d^n + (1 - \beta) V_d^n,$$

$$V_d^n = \frac{(1 + \overline{\pi}) w_d^n}{\beta}.$$

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Market clearing: labor

Inventors

- Supply:

$$R_d = \sum_o \eta^R_{od} \overline{R}_o$$

- Demand:

Workers

- Supply:

$$L_d = \sum_o \eta^L_{od} \overline{L}_o$$

- Demand: not necessary due to Walras's Law

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Trade balance

- Income:

$$Y_o = \frac{(1+\overline{\pi})\left(w_o^L L_o + w_o^R R_o\right)}{\beta}$$

- Expenditure:

$$X_o = \sum_d \chi_{od} X_d$$

- Trade balance:

$$Y_o = X_o$$

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Market clearing: housing

- Supply:

$$H_o = \overline{H}_o$$

- Demand:

$$r_o = \frac{(1-\beta)\,Y_o}{H_o}$$

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Equilibrium with R&D subsidies

Given the exogenous distribution of workers and inventors across locations $\left\{\overline{R}_o, \overline{L}_o\right\}_{\forall o \in \mathcal{S}}$, fixed supply of housing $\left\{\overline{H}_o\right\}_{\forall o \in \mathcal{S}}$, location fundamentals $\left\{\mathcal{Z}_o, \mathcal{A}_o\right\}_{\forall o \in \mathcal{S}}$, location amenities $\left\{\mathcal{B}_o^R, \mathcal{B}_o^L\right\}_{\forall o \in \mathcal{S}}$, migration costs $\left\{\mu_{od}^R, \mu_{od}^L\right\}_{\forall o, d \in \mathcal{S}, \mathcal{S}}$, trade costs $\left\{\tau_{od}\right\}_{\forall o, d \in \mathcal{S}, \mathcal{S}}$, R&D subsidies $\left\{s_o\right\}_{\forall o \in \mathcal{S}}$, and parameters, *an equilibrium with R&D subsidies is a set of wages* $\left\{w_o^R, w_o^L\right\}_{\forall o \in \mathcal{S}}$, *housing rent* $\left\{r_o\right\}_{\forall o \in \mathcal{S}}$, *prices* $\left\{P_o\right\}_{\forall o \in \mathcal{S}}$, *quantities* $\left\{L_o, R_o, H_o, Q_o\right\}_{\forall o \in \mathcal{S}}$, *and quality* $\left\{Z_o\right\}_{\forall o \in \mathcal{S}}$ *such that*

1. *workers and inventors maximize utility*
2. *firms maximize profits*
3. *workers and inventors labor markets clear*
4. *housing market clears*
5. *government's budget is balanced*
6. *trade is balanced*

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Migration costs: $\left\{\mu^R_{od}, \mu^L_{od}\right\}$

- Iceberg migration costs:

$$\mu^n_{od} = \rho^n_0 dist_{od}^{\rho^n_1} \exp\left(-\frac{\epsilon^n_{od}}{\kappa}\right)$$

- $\{\rho^n_0\}$:
  - Targets: 10-year average migration rates
  - $\left\{\widehat{\rho^L_0}, \widehat{\rho^R_0}\right\} = \{25\%, 26.4\%\}$
- $\{\rho^n_1\}$: Elasticities of migration costs to distance
  - Migration gravity equations:

Results

$$\log\left(\eta^n_{od,t}\right) = \iota + \iota_{o,t} + \iota_{d,t} - \rho_n\kappa \log\left(dist_{od}\right) + \epsilon^n_{od,t}, \;\; n = \{R, L\}$$

  - Given $\kappa = 2.12$ (Peters, 2022), PPML:

$$\left\{\rho^R_1, \rho^L_1\right\} = \left\{\frac{1.254}{2.12}, \frac{1.277}{2.12}\right\}$$

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Trade costs: τ_{od}

- Iceberg trade costs:
$$\tau_{od} = \xi_0 dist_{od}^{\xi_1}$$
- ξ_0 :
  - Target: 50% share of total intra-regional trade (Ramondo et al., 2016)
- ξ_1 : Elasticity of trade costs to distance
  - No data on internal data
  - Given $\sigma = 2.5$ (Broda and Weinstein, 2006), follow Krebs and Pflüger (2021): $\xi_1 = \frac{1.56}{\sigma - 1}$

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Location fundamentals $\{\mathcal{A}_o, \mathcal{Z}_o\}$

Given parameter values $\{\psi, \widetilde{\gamma}\}$, and data on wages and population $\left\{w_o^R, R_o\right\}$, there is a unique set of values for location fundamentals for R&D $\{\mathcal{Z}_o\}$ that that is consistent with the aggregate demand for inventors. Then, given trade costs $\{\tau_{od}\}$, parameter values $\{\psi, \sigma, \widetilde{\gamma}\}$, and data on wages and population $\left\{w_o^R, w_o^L, R_o, L_o\right\}$, there is a unique set of values for location fundamental for production $\{\mathcal{A}_o\}$ that is consistent with the data.

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Location amenities $\left\{\mathcal{B}_o^R, \mathcal{B}_o^L\right\}$

Given the exogenous distribution of workers and inventors across locations $\left\{\overline{R}_o, \overline{L}_o\right\}_{\forall o \in \mathcal{S}}$, fixed supply of housing $\left\{\overline{H}_o\right\}_{\forall o \in \mathcal{S}}$, trade costs $\{\tau_{od}\}$, migration costs $\left\{\mu_{od}^R, \mu_{od}^L\right\}$, fundamental location productivities $\{\mathcal{Z}_o, \mathcal{A}_o\}$, parameter values $\{\alpha, \psi, \kappa, \sigma, \beta\}$, and data on wages and population $\left\{w_o^R, w_o^L, R_o, L_o\right\}$, there is a unique set of values for fundamental location amenities $\left\{\mathcal{B}_o^R, \mathcal{B}_o^L\right\}$ that is consistent with the data.

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Planner problem

$$\max \left(\frac{\overline{L}}{\overline{L}+\overline{R}}\right)\sum_o \overline{U}_o^L + \left(\frac{\overline{R}}{\overline{L}+\overline{R}}\right)\sum_o \overline{U}_o^R,$$

where

$$\overline{U}_o^L = \Gamma\left(\frac{\kappa-1}{\kappa}\right)\left(\sum_d \left(\frac{U_d^L}{\mu_{od}^L}\right)^{\kappa}\right)^{\frac{1}{\kappa}},$$

$$\overline{U}_o^R = \Gamma\left(\frac{\kappa-1}{\kappa}\right)\left(\sum_d \left(\frac{U_d^R}{\mu_{od}^R}\right)^{\kappa}\right)^{\frac{1}{\kappa}},$$

and

- Labor market clears
- Inventor market clears
- Housing market clears
- Final good market clears
- Intermediate input market clears

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