Firm Productivity Growth and its Relationship to the Knowledge of New Workers

Michael Kirker
University of Chicago

Statistics New Zealand Disclaimer

Access to the data presented was managed by Statistics New Zealand under strict micro-data access protocols and in accordance with the security and confidentiality provisions of the Statistic Act 1975. Their/Our findings are not Official Statistics. The opinions, findings, recommendations, and conclusions expressed are those of the author(s)/researchers, not Statistics NZ, the Treasury, or the Ministry of Business, Innovation and Employment.

The results are based in part on tax data supplied by Inland Revenue to Statistics NZ under the Tax Administration Act 1994. This tax data must be used only for statistical purposes, and no individual information may be published or disclosed in any other form, or provided to Inland Revenue for administrative or regulatory purposes.

Any person who has had access to the unit record data has certified that they have been shown, have read, and have understood section 81 of the Tax Administration Act 1994, which relates to secrecy. Any discussion of data limitations or weaknesses is in the context of using the IDI for statistical purposes, and is not related to the data's ability to support Inland Revenue's core operational requirements.

Motivation – Background

- New Knowledge is regarded as an important driver of long-run growth
- Only a relatively small number of firms actually carry out R&D – suggesting the for a majority of firms, acquisition of knowledge from outside the firm is important
- Labor mobility has often been discussed as one of the main channels through which knowledge can spill over between firms

2013 Business Operations Survey:

52 percent of innovating firms reported that new workers were a source of ideas for innovation

Research question

Aim:

How is productivity growth related to a firm's exposure to outside knowledge?

- Is the relationship consistent with knowledge spillover or other channels of influence?
- Quantify the importance of where workers are hires from
  - Useful for calibrating models of knowledge spillover (see Kirker, 2017)

Approach

- Use firm-level data to construct measure of firm productivity and map the flow of workers between firms
- Construct a proxy for a firm's exposure to outside knowledge — productivity of the firms workers are hired from
- Relate *productivity growth* to the firms exposure to outside knowledge
- Compare the model's correlations with the predictions from some well known channels through which new worker's knowledge can affect firm productivity

Preview of Findings

Baseline:

- Productivity growth is significantly correlated with the relative productivity level of the firms from which new workers are hired.
- The strength of this relationship differs according to:
  - Productivity measure used
  - Whether the sending firm has higher or lower productivity than the hiring firm

Preview of Findings

- If a firm hires 10% of its workers from **more** productive firms, raising the average productivity of the firms workers are sourced from by 1%:
  - Raises *MFP* growth by 0.35 percentage points
  - Raises *labor productivity* growth by 0.48 percentage points
- If a firm hires 10% of its workers from **less** productive firms, raising the average productivity of the firms workers are sourced from by 1%:
  - Raises *MFP* growth by 0.37 percentage points
  - Raises *labor productivity* growth by 0.15 percentage points

Related literature

Measure exposure through number of hires

- Parrotta and Pozzoli (2012), Serafinelli (2015), Stockinger and Wolf (2016)
- Between MNE and domestic firms: Görg and Strobl (2005) and Balsvik (2011)

Measure exposure through productivity differences

- Stoyanov and Zubanov (2012)

This Paper's Contribution

To empirical literature:

- Provide most comprehensive coverage of productivity and industries
- Control for exposure to hires from outside the scope
  - Also distinguish intensive from extensive margin in productivity gap
- Use of survey data as control for causality

To endogenous growth:

- Provides estimates suitable for calibrating models of knowledge spillover (see Kirker, 2017)

Model

Exposure to Outside Productivity

Construct a proxy for a firm's exposure to other productivity through new hires

$$\text{Exposure}_{i,t} = \beta_{agg} \overbrace{\frac{\sum_{n \in \mathcal{N}_i, t-1} \left[\ln(A_{n,\tau-\delta}) - \ln(A_{i,t-1-\delta})\right]}{H_{i,s_1,t-1}} \frac{H_{i,s_1,t-1}}{L_{i,s_1,t-1}}}^{\text{productivity gap}}$$

$$+ \sum_{s \in \mathcal{S}_{i,t-1}} \lambda_s \underbrace{\frac{H_{i,s,t-1}}{L_{i,t-1}}}_{\text{hiring intensity}}$$

Exposure to Outside Productivity – Disaggregated

- Often will be convenient to disaggregate productivity gap into sub-groups of hires
- For example hires from more and less productive firms:

$$\begin{aligned}\text{Exposure}_{i,t} = &\beta_{more} \frac{\sum_{n \in \mathcal{N}_{i,t-1}} \mathbb{D}_n \left[\ln(A_{n,\tau-\delta}) - \ln(A_{i,t-1-\delta})\right]}{H_{i,s_1,t-1}} \frac{H_{i,s_1,t-1}}{L_{i,s_1,t-1}} \\ &\beta_{less} \frac{\sum_{n \in \mathcal{N}_{i,t-1}} (1 - \mathbb{D}_n) \left[\ln(A_{n,\tau-\delta}) - \ln(A_{i,t-1-\delta})\right]}{H_{i,s_2,t-1}} \frac{H_{i,s_2,t-1}}{L_{i,s_2,t-1}} \\ &+ \sum_{s \in \mathcal{S}_{i,t-1}} \lambda_s \frac{H_{i,s,t-1}}{L_{i,t-1}}\end{aligned}$$

$\mathbb{D}_n = 1$ denotes worker from coming from a more productive firm $(\ln(A_{n,\tau-\delta}) > \ln(A_{i,t-1-\delta}))$

Model estimation approach

Dynamic panel model – Estimated using first difference

Model:

$$\begin{aligned}\Delta \ln A_{i,j,t} =& \text{Exposure}_{i,t} + \gamma\, \Delta Q_{i,t} + \delta\, \Delta \text{ExTurn}_{i,t} \\ &+ \sum_{l=1}^{L} \alpha_{A,l}\, \Delta \ln A_{i,j,t-l} + \theta_{j,t} + \varepsilon_{i,t}\end{aligned}$$

- $\varepsilon_{i,t}$ correlated with $\Delta \ln A_{i,j,t-1}$, so instrument $\Delta \ln A_{i,j,t-1}$ with $\ln A_{i,j,t-2}$ (Nickell bias)

Data

Data sources

Sample period 2001 to 2013

Firm data — Longitudinal Business Database (LBD)

- All economic significant firms in the measured economy (39 industries)
- Private for Profit (PFP) firms
- Tax filings and survey data
- Adjustments made for changing ownership structure
- Firm productivity estimates (VA and MFP)

Data sources

Labor data — Integrated Data Infrastructure (IDI)

- Pay As You Earn (PAYE) tax data
- Monthly income from all jobs
- Full Time Equivalent labor estimated
- Used to:
  1. Construct measure of worker quality (using some demographic info)
  2. Map the movement of workers between firms

Summary stats – Firms

	All firms			Firms who hire			Firms who do not hire		
	Mean	**Median**	**S.D.**	**Mean**	**Median**	**S.D.**	**Mean**	**Median**	**S.D.**
Labor productivity									
log V.A. per worker	11.102	11.094	N.A.	11.101	11.093	N.A.	11.176	11.165	N.A.
Growth rate V.A. per worker (%)	-0.004	0.000	0.432	-0.003	0.001	0.432	-0.040	-0.019	0.388
Productivity gap									
Aggregate gap	0.005	0	0.208	0.005	0	0.209	0	0	0
more prod. firms gap	0.064	0.015	0.164	0.065	0.016	0.165	0	0	0
less prod. firms gap	-0.060	-0.022	0.123	-0.061	-0.023	0.124	0	0	0
Labor force									
Total FTE units of labor	56.230	17.961	255.994	56.953	18.166	258.128	14.248	12.181	8.657
Share of FTE from new hires	0.194	0.155	0.169	0.198	0.157	0.169	0	0	0
Share of FTE from exiting workers	0.172	0.136	0.150	0.174	0.138	0.150	0.086	0.042	0.165
Excess (annual) turnover	0.514	0.457	0.329	0.522	0.462	0.325	0.019	0	0.054
New Hires									
No. of new employees	22.070	7	101.667	22.448	7	102.498	0	0	0
Share of hires from brand new workers	0.001	0	0.018	0.001	0	0.018	0	0	0
Share of hires from non-market	0.116	0.062	0.166	0.116	0.062	0.165	0	0	0
Share of hires from small firms (L<10)	0.288	0.250	0.232	0.288	0.250	0.231	0	0	0
Share of hires from missing prod. data	0.102	0.051	0.154	0.102	0.053	0.154	0	0	0
Share of hires from PFP	0.489	0.500	0.257	0.489	0.500	0.257	0	0	0
within same industry	0.131	0.061	0.180	0.131	0.062	0.180	0	0	0
more productive sources	0.205	0.167	0.219	0.205	0.167	0.219	0	0	0
Obs.	126048	0	0	124146			1902		

Firm productivity transitions (VApw)

Firm's current prod. decile	Firm's previous productivity decile										Missing prod data	L<10
	1	2	3	4	5	6	7	8	9	10		
1	0.32	0.13	0.05	0.04	0.03	0.02	0.02	0.01	0.01	0.01	0.27	0.1
2	0.11	0.31	0.14	0.05	0.02	0.02	0.01	0.01	0.01	0	0.22	0.1
3	0.05	0.13	0.26	0.15	0.06	0.03	0.02	0.01	0	0	0.2	0.09
4	0.04	0.05	0.14	0.22	0.15	0.07	0.03	0.02	0.01	0	0.2	0.09
5	0.03	0.02	0.05	0.14	0.23	0.14	0.06	0.03	0.01	0.01	0.18	0.09
6	0.02	0.02	0.03	0.06	0.14	0.22	0.16	0.06	0.02	0.01	0.18	0.07
7	0.01	0.01	0.01	0.03	0.06	0.14	0.24	0.16	0.05	0.01	0.19	0.07
8	0.01	0.01	0.01	0.01	0.03	0.06	0.15	0.27	0.17	0.03	0.18	0.07
9	0.01	0	0	0.01	0.01	0.02	0.05	0.15	0.35	0.13	0.19	0.07
10	0.01	0	0	0	0	0.01	0.01	0.03	0.12	0.57	0.19	0.06

Summary stats – Workers

Variable	All new hires Mean	All new hires Median	All new hires S.D.	New hires from more productive firms Mean	New hires from more productive firms Median	New hires from more productive firms S.D.	New hires from less productive firms Mean	New hires from less productive firms Median	New hires from less productive firms S.D.
A) New worker's characteristics (at the hiring firm) relative to incumbent workers									
Real earnings percentile	0.450	0.407	0.309	0.422	0.369	0.303	0.464	0.438	0.305
FTE supplied relative to avg. incument	0.903	1.003	0.690	0.904	1.002	0.616	0.918	1.008	0.715
Age relative to avg. incumbent	0.889	0.825	0.343	0.899	0.835	0.343	0.860	0.793	0.332
Worker quality percentile	0.490	0.478	0.299	0.460	0.429	0.293	0.511	0.500	0.295
Number of jobs relative to avg. incumbent	1.141	0.975	0.533	1.135	0.971	0.535	1.130	0.975	0.486
Obs.	4094400			1154500			1335200		
B) New worker's characteristics (at last main job) relative to the workers who stays									
Real earnings percentile	0.450	0.407	0.309	0.422	0.369	0.303	0.805	0.713	0.612
FTE supplied relative to avg. stayer	0.920	1.001	1.456	0.980	1.015	0.939	0.883	1	0.858
Age relative to avg. stayer	0.879	0.813	0.345	0.889	0.825	0.345	0.850	0.783	0.334
Worker quality percentile	0.490	0.478	0.299	0.460	0.429	0.293	0.511	0.500	0.295
Number of jobs relative to avg. stayer	1.145	0.972	0.546	1.131	0.965	0.543	1.139	0.974	0.504
Obs.	4005200			1131200			1314900		
C) New worker's characteristics at their new job relative to their own characteristics at the last main job									
Real earning per FTE	1.119	1.025	0.494	1.064	1.002	0.459	0.464	0.438	0.305
FTE supplied: new job relative to old job	2.346	1	228.217	2.178	1	205.699	2.532	1	330.921
No. of months between jobs	5.484	0	13.167	4.823	0	11.572	4.630	0	11.539
Prob. working in same industry	0.226	0	0.418	0.284	0	0.451	0.275	0	0.447
Obs.	4202000	0	0	1180200	0	0	1367800	0	0
0	0			0			0		

Worker productivity transitions (VApw)

Hiring firm's prod. decile	Source of new employee hires: PFP productivity decile 1	2	3	4	5	6	7	8	9	10	New Arrivals	Non Market	Firms with L<5	PFP miss. data
1	0.05	0.08	0.05	0.05	0.04	0.04	0.04	0.04	0.04	0.04	0.00	0.16	0.30	0.08
2	0.05	0.08	0.05	0.05	0.04	0.04	0.04	0.04	0.03	0.03	0.00	0.16	0.31	0.08
3	0.04	0.07	0.06	0.06	0.04	0.04	0.03	0.03	0.03	0.03	0.00	0.16	0.32	0.08
4	0.04	0.06	0.05	0.05	0.05	0.04	0.04	0.04	0.04	0.04	0.00	0.14	0.33	0.08
5	0.04	0.06	0.05	0.05	0.05	0.04	0.04	0.05	0.04	0.04	0.00	0.14	0.32	0.08
6	0.04	0.06	0.04	0.04	0.04	0.04	0.04	0.05	0.05	0.04	0.00	0.13	0.33	0.08
7	0.04	0.06	0.04	0.04	0.04	0.04	0.05	0.05	0.05	0.05	0.00	0.13	0.32	0.08
8	0.04	0.06	0.04	0.04	0.04	0.04	0.05	0.05	0.05	0.06	0.00	0.13	0.32	0.08
9	0.04	0.05	0.03	0.03	0.04	0.04	0.04	0.06	0.06	0.08	0.00	0.13	0.31	0.08
10	0.04	0.05	0.03	0.03	0.03	0.03	0.04	0.05	0.06	0.13	0.00	0.14	0.28	0.09

Baseline Results

Baseline Results

	Trans-log	**Value-added p.w.**
Productivity gap, hires from (β):		
More prod. firms	0.354***	0.480***
	(0.068)	(0.098)
Less prod. firms	0.374***	0.153***
	(0.056)	(0.030)
Hire intensity (λ):		
More prod. firms	-0.037*	-0.200***
	(0.021)	(0.057)
Less prod. firms	0.004	-0.117***
	(0.019)	(0.027)
Parameter tests:		
$\Pr(\beta_{more} = \beta_{less})$	0.808	0.001
$\Pr(\lambda_{more} = \lambda_{less})$	0.174	0.237
Obs.	38037	37269

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Baseline Results – Capital intensity

	Capital-Labor
Input intensity gap, hires from (β):	
More input-intensive firms	0.047***
	(0.017)
Less input-intensive firms	0.021
	(0.024)
Hire intensity (λ):	
More input-intensive firms	0.071**
	(0.031)
Less input-intensive firm	-0.182***
	(0.035)
Parameter tests:	
$\Pr(\beta_{more} = \beta_{less})$	0.369
$\Pr(\lambda_{more} = \lambda_{less})$	0.000
Obs.	28260

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Predictions: Worker Quality

- Positive assortative matching – more productive firms have better workers on average
  - Better selection ability
  - Better on-the-job training
- Productivity of previous employer should act as a signal for worker quality

Prediction

$\beta_{more} = \beta_{less} > 0$

Predictions: Knowledge Spillover

- Workers learn productive knowledge on the job
- Workers from more productive firms likely to bring better knowledge to the hiring firm
  - Boost to productivity growth
- Ideas do not have to be implemented – Less productive ideas get discarded
  - No effect on productivity growth

Predictions

1. $\beta_{more} > 0$
2. $\beta_{less} = 0$

Exposure From The Same Industry

Disaggregate by relative productivity and relative industry:

- Knowledge or training might be industry-specific

$$\begin{aligned}\text{Exposure}_{i,t} = & \sum_{\text{ind}\in\{\text{same},\text{diff}\}} \beta_{more,ind} \frac{\sum_{n\in\mathcal{N}_j,t-1} \mathbb{D}_{\text{ind}}(n)\mathbb{D}_n[\ln(A_{n,\tau-\delta}) - \ln(A_{i,t-1-\delta})]}{L_{i,t-1}} \\ & + \sum_{\text{ind}\in\{\text{same},\text{diff}\}} \beta_{less,\text{ind}} \frac{\sum_{n\in\mathcal{N}_j,t-1} \mathbb{D}_{\text{ind}}(n)(1-\mathbb{D}_n)[\ln(A_{n,\tau-\delta}) - \ln(A_{i,t-1-\delta})]}{L_{i,t-1}} \\ & + \sum_{s\in\mathcal{S}_{i,t-1}} \lambda_s \frac{H_{i,s,t-1}}{L_{i,t-1}}\end{aligned}$$

Exposure From The Same Industry

	Trans-log			Value-added p.w.		
	Baseline	Productivity gaps by ind.		Baseline	Productivity gaps by ind.	
		3-digit	1-digit		3-digit	1-digit
Productivity gap, hires from (β):						
More prod. firms	0.354***			0.480***		
	(0.068)			(0.098)		
Same ind.		0.311**	0.287***		1.016***	0.926***
		(0.123)	(0.105)		(0.230)	(0.164)
Diff. ind.		0.373***	0.390***		0.367***	0.326***
		(0.090)	(0.097)		(0.123)	(0.121)
Less prod. firms	0.374***			0.153***		
	(0.056)			(0.030)		
Same ind.		0.278***	0.314***		0.188***	0.156***
		(0.103)	(0.079)		(0.068)	(0.052)
Diff. ind.		0.415***	0.418***		0.139***	0.152***
		(0.071)	(0.086)		(0.035)	(0.039)
Parameter tests:						
$\Pr(\beta_{more,same} = \beta_{less,same})$		0.825	0.832		0.001	0.000
$\Pr(\beta_{more,diff} = \beta_{less,diff})$		0.712	0.824		0.064	0.159
$\Pr(\beta_{more,same} = \beta_{more,diff})$		0.724	0.517		0.029	0.005
$\Pr(\beta_{less,same} = \beta_{less,diff})$		0.302	0.406		0.531	0.955
Obs.	28260	28260	28260	37269	37269	37269

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Exposure by Worker Tenure

Does a worker's tenure at the previous employer matter for the hiring firm's productivity growth?

- **Knowledge spillover** – Longer tenure provides more opportunities to absorb knowledge
- **Unmeasured worker quality** – mixed predictions
  - Training – more opportunities to improve
  - Screening – shouldn't be affected by tenure

Disaggregate worker flow further by tenure at sending firm

- Long = 12 or more months
- Short = less than 12 months

app

Exposure by Worker Tenure

	Trans-log		Value-added per worker	
	Baseline	**By Tenure**	**Baseline**	**By Tenure**
Productivity gap, hires from (β):				
More prod. firms	0.354***		0.480***	
	(0.068)		(0.098)	
with long tenure		0.325***		0.375***
		(0.116)		(0.138)
with short tenure		0.343***		0.550***
		(0.091)		(0.155)
Less prod. firms	0.374***		0.153***	
	(0.056)		(0.030)	
with long tenure		0.569***		0.187***
		(0.087)		(0.053)
with short tenure		0.226***		0.116**
		(0.086)		(0.045)
Parameter tests:				
$\Pr(\beta_{more,long} = \beta_{less,long})$		0.097		0.200
$\Pr(\beta_{more,short} = \beta_{less,short})$		0.344		0.006
$\Pr(\beta_{more,long} = \beta_{more,short})$		0.915		0.445
$\Pr(\beta_{less,long} = \beta_{less,short})$		0.013		0.350
Obs.	38037	38037	37269	37269

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Exposure by Worker Tenure – Capital Intensity

	Baseline	**By Tenure**
Input intensity gap, hires from (β):		
More prod. firms	0.047***	
	(0.017)	
with long tenure		0.138***
		(0.038)
with short tenure		-0.011
		(0.033)
Less input-intensive firms	0.021	
	(0.024)	
with long tenure		0.077*
		(0.042)
with short tenure		0.071
		(0.050)
Parameter tests:		
$\Pr(\beta_{more,long} = \beta_{less,long})$		0.273
$\Pr(\beta_{more,short} = \beta_{less,short})$		0.990
$\Pr(\beta_{more,long} = \beta_{more,short})$		0.014
$\Pr(\beta_{less,long} = \beta_{less,short})$		0.106
Obs.	28260	28260

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Robustness and Extensions

Reverse Causality – BOS

Reverse causality – What if firm productivity changes drive hiring?

- Business Operations Survey
  - Nationally representative survey
  - Every second year includes an innovation module

Business Operations Survey (BOS) Question:

Were new staff important as a source of ideas or information for innovation?

Reverse Causality – BOS

	Trans-log		Value-added	
Workers are a source of innovation ideas:	**True**	**False**	**True**	**False**
Productivity gap, hires from (β):				
More prod. firms	0.539***	0.510	0.709***	0.332***
	(0.106)	(0.470)	(0.199)	(0.113)
Less prod. firms	0.476**	0.471**	0.225**	-0.078
	(0.223)	(0.239)	(0.099)	(0.132)
Hire intensity (λ):				
More prod. firms	-0.116***	-0.082	-0.413***	-0.000
	(0.044)	(0.211)	(0.136)	(0.122)
Less prod. firms	0.090	0.098	-0.060	-0.210
	(0.084)	(0.078)	(0.099)	(0.128)
Parameter tests:				
$\Pr(\beta_M = \beta_L)$	0.763	0.937	0.017	0.012
$\Pr(\lambda_M = \lambda_L)$	0.062	0.482	0.070	0.231
Obs.	1170	795	1161	783

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Reverse Causality – Levinsohn-Petrin

Observing the (expected) firm productivity before hiring would control for the direction of causality

Structural approach – Estimate innovation shocks observed by the firm

- Levinsohn & Petrin (2003)
- Olley & Pakes (1996)

Reverse Causality – Levinsohn-Petrin

	Cobb-Douglas	Levinsohn-Petrin
Productivity gap, hires from (β):		
More prod. firms	0.271***	0.211***
	(0.065)	(0.037)
Less prod. firms	0.374***	0.213***
	(0.054)	(0.056)
Hire intensity (λ):		
More prod. firms	-0.012	0.021
	(0.028)	(0.025)
Less prod. firms	0.047*	-0.010
	(0.026)	(0.036)
Parameter tests:		
$\Pr(\beta_{more} = \beta_{less})$	0.217	0.983
$\Pr(\lambda_{more} = \lambda_{less})$	0.145	0.501
Obs.	28260	38037

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Blundell-Bond Additional Instruments

- $\Delta \ln A_{i,j,t-1}$ should be an important control in the model
- $\ln A_{i,j,t-2}$ is not the only instrument useable for $\Delta \ln A_{i,j,t-1}$
- Blundell-Bond methodology uses lagged levels and differences

Blundell-Bond Additional Instruments

	Trans-log		Value-added p.w.	
	Baseline	**Blundell-Bond**	**Baseline**	**Blundell-Bond**
Productivity gap, hires from (β):				
More prod. firms	0.354***	0.250***	0.480***	0.515***
	(0.068)	(0.093)	(0.098)	(0.124)
Less prod. firms	0.374***	0.296***	0.153***	0.172***
	(0.056)	(0.075)	(0.030)	(0.043)
Hire intensity (λ):				
More prod. firms	-0.037*	-0.027	-0.200***	-0.193***
	(0.021)	(0.021)	(0.057)	(0.063)
Less prod. firms	0.004	0.007	-0.117***	-0.108***
	(0.019)	(0.018)	(0.027)	(0.027)
Obs.	38037	50874	37269	49920

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Conclusions

Conclusions

Baseline results:

- Prod. growth is significantly correlated with the relative prod. level of the firms from which new workers are hired.
- Multi-factor productivity: consistent with worker quality (positive assortative matching)
- Labor productivity: consistent with knowledge spillover + worker quality

Extensions:

- Capital-intensity related to knowledge spillover
- Robust to attempts to control for reverse causality