Technological Innovation and Labor Income Risk

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Motivation

- Income inequality has risen sharply over the last few decades.
  - Much of increase in inequality between firms (Song et al. 2017).
- Human capital accounts for significant source of wealth.
  - Traditional view: labor income safe, limited pass through of firm shocks to workers. To be debated.
- What are the main drivers? We focus one particular channel:
  - Technological innovation often involves creative destruction (Schumpeter, 1942): new firms / products / technologies displace existing ones.
  - If workers share some of their profits with workers, these workers will bear part of the cost.
- How does technological innovation by firms contribute to labor income risk faced by workers? Overall inequality?

What we do

- We combine direct measures of innovative activity from patent data and stock returns with data on worker earnings (SSA records)
- Study how the distribution of workers' labor income shifts after major technological advances by their employers and/or their competitors
  - We estimate quantile regressions rather than only average effects
- Innovation likely has heterogenous impact on workers, may increase overall (mostly uninsurable) income risk
  - Focusing on average worker obscures the distribution of gains and losses.
- Caveats
  1. we document statistical associations, not causal relations
  2. not about automation; focus on producers (vs users) of new technologies
  3. 'risk' refers ex-post heterogeneity in outcomes conditional on observables

What we find

- Innovation by the firm increases profits and average wages for incumbent workers; innovation by competitors has the opposite effect.
  - Implied profit-sharing elasticities are greater on the downside
- Gains and losses concentrated on a subset of incumbent workers
  - Innovation by the firm followed by a more right-skewed distribution of earnings growth
  - Innovation by competitors leads to more negatively skewed distribution of future earnings growth.
- The increase in the left tail is primarily driven by separations
- Magnitudes larger for higher-paid workers.
- Process innovation associated with greater earnings dispersion
- Estimates account for sizable portion of increase in between-firm (& within-firm) inequality

Theoretical motivation

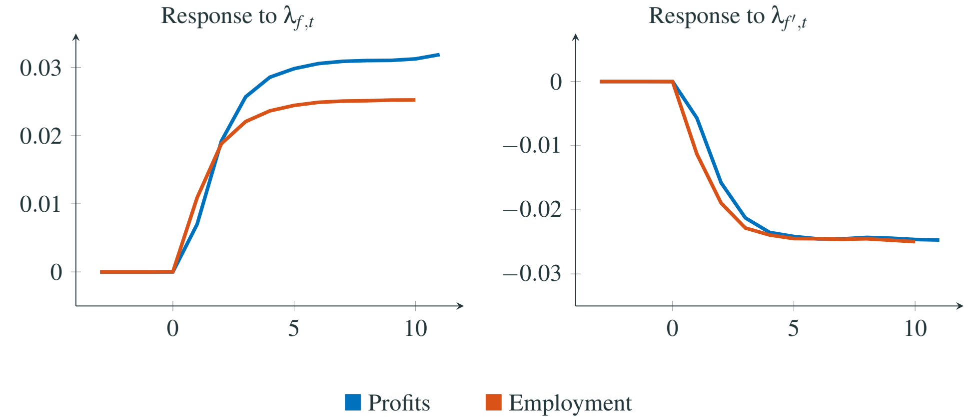
Simple model based on Aghion and Howitt (1992) and Grossman and Helpman (1991) with firm-specific human capital:

- Firms are collections of product lines / jobs.
- Each worker associated w/ single product line, receives wage proportional to product quality.
- Firms innovate at rate $\lambda_{f,t} \in \{\lambda_L, \lambda_H\}$. Innovating firms
  - with prob. μ they improve quality of existing products
    - with prob. p, worker is retained, replaced otherwise
  - with prob. $1-\mu$ steal a product from another firm; worker is replaced.
- Replaced workers become unemployed, receive outside option.

Model impulse responses: Firm outcomes

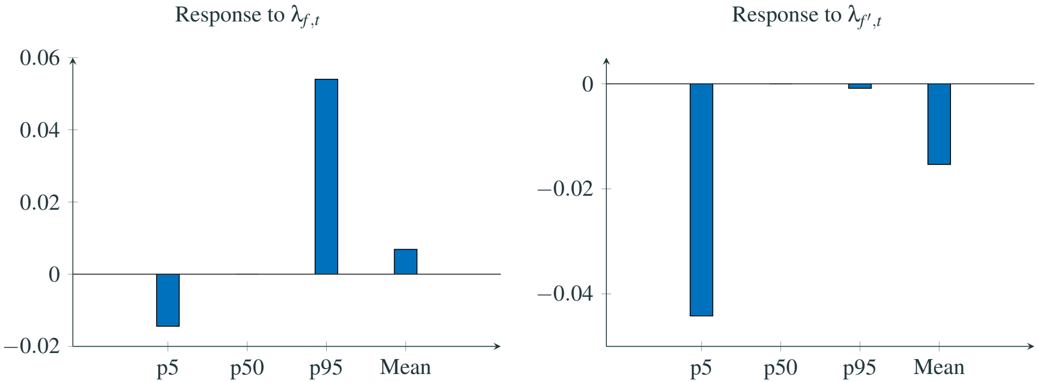
Numerical Example: 2 firms, f and f'

Response for firm f to an increase in $\lambda_{f,t}$ or $\lambda_{f',t}$



Model impulse responses: Worker outcomes

Response of the distribution of earnings growth $\log\left(w_{j,t+T}/w_{j,t}\right)$



Measuring technological innovation

- How to measure 'technological innovation' is not obvious
- Patents seem like a natural candidate. By definition, they relate to new inventions—though not all valuable inventions are patentable.
- More importantly, not all patents are equally valuable inventions.
  - proliferation of patents with no value (Jaffe & Lerner 2004)
  - pro-patent shift in US policy (Hall and Zeidonis 2001)
- Easy to come up with examples of not so useful patents.
- Need to weigh innovation outcomes by their economic value.
  - Kogan, Papanikolaou, Seru, and Stoffman (QJE, 2017) estimate the value of patents using firm's stock market reaction to patent issues as an estimate of the (private) value of patents. KPSS value estimates correlate with measures of 'scientific value'. Example Trading Volume Citations Placebo

Data

- SSA data: 10% random sample of worker annual earnings.
  - Date range: 1980-2013; males, ages 25-58; minimum earnings level; exclude workers with substantial self-employment income
  - Workers matched to public firms based on highest earnings in given year. (Matched sample has 14m workers. Characteristics: Firms Workers)
- Construct age-adjusted income between periods t and $t+k$

$$w^i_{t,t+k} \equiv \log\left(\frac{\sum_{j=0}^{k} \text{W2 wage}_{i,t+j}}{\sum_{j=0}^{k} D(\text{age}_{i,t+j})}\right)$$

- Main outcome variable is growth in (cumulative) log earnings

$$Y_{i,t:t+h} \equiv w^i_{t,t+h} - w^i_{t-2,t}$$

Our specification emphasizes permanent income changes Details

Innovation, firm profitability and worker earnings

- Estimate:

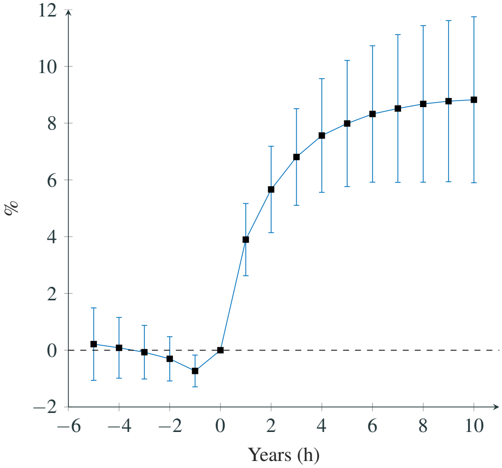
$$Y_{i,t:t+h} = a_h \, \text{Firm Innovation}_{f,t} + b_h \, \text{Competitor Innovation}_{f,t} + c_h Z_{ft} + u_{ft+h}.$$

- Firm- and worker-level regressions:
  - Firm profitability. Controls: firm size (assets); firm idiosyncratic volatility; industry; and time FE
  - Worker earnings. Controls: as above, plus flexible parametric functions of age; earnings rank within industry; earnings rank within firm; firm rank $\times$ polynomials in lagged income growth rates
- Weigh worker-level regressions by inverse of firm-year employment count (allows us to compare across firm- and worker-level regressions)
- Allow for serially correlated errors at the firm level (bootstrap). Details

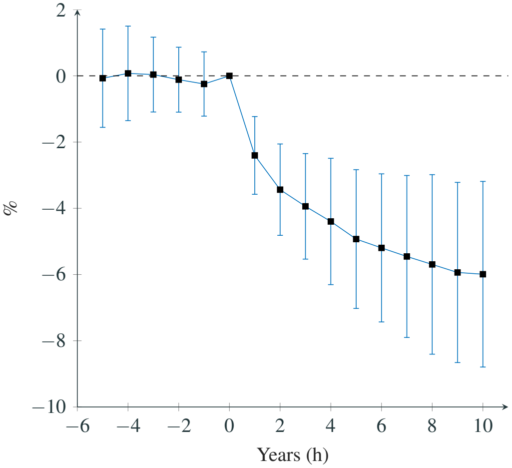
Innovation and firm outcomes

Response of profitability to 1 SD shock to

Own innovation



Competitor innovation



Firm profitability, worker earnings and innovation

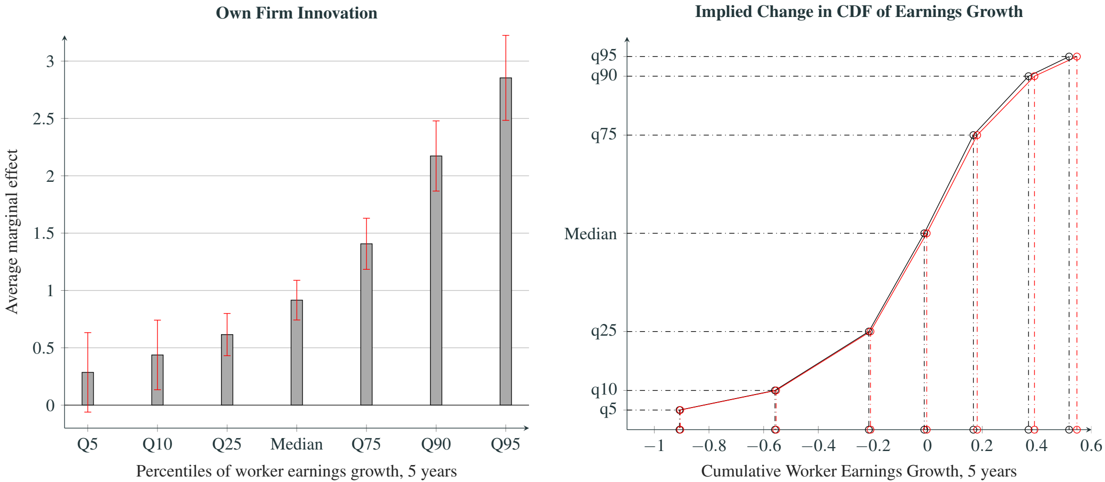
A. Market Values	i. Firm Profitability			ii. Worker Earnings		
Horizon (years)	(3)	(5)	(10)	(3)	(5)	(10)
Firm Innovation,	6.81	7.99	8.82	1.38	1.38	1.07
market value (A_f^{sm})	(7.83)	(7.04)	(5.92)	(15.46)	(11.33)	(10.01)
Competitor Innovation,	-3.94	-4.93	-5.99	-1.45	-1.88	-2.28
market value ($A_{I\setminus f}^{sm}$)	(-4.85)	(-4.61)	(-4.19)	(-5.42)	(-8.45)	(-9.27)
R^2	0.197	0.220	0.233	0.045	0.050	0.054

Note: Independent variables scaled to unit standard deviation

- An increase in own firm innovation followed by an increase in firm profits and an increase in worker earnings for the incumbent worker.
- An increase in competitor innovation leads to lower firm profits and future earnings for incumbent workers.

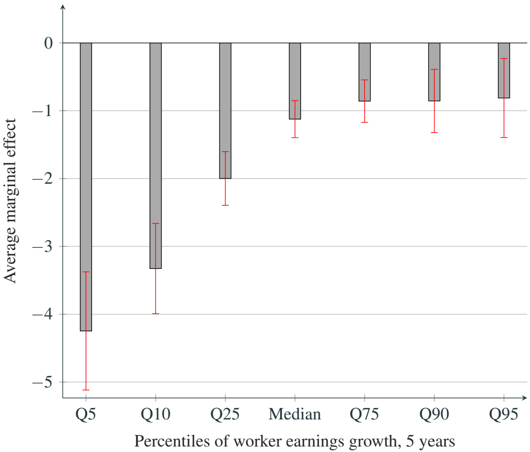
Are firms insuring workers?

- Focus on 5-year estimates.
  - Own firm coefficients imply a rent-sharing elasticity of 1.38 / 7.99 = 0.17 (comparable to most estimates in literature)
  - Competitor coefficients however imply an elasticity of 1.88 / 4.93 = 0.38
- One interpretation: employees capture $\sim 1/5$ of the benefits of innovation, as firm owners and workers share risks (e.g., Guiso, Pistaferri, & Schivardi, 2005)
- Perhaps. But note that,
  1. Employees capture a larger share of the costs than the profits (not very good insurance...)
  2. Above statements hold on average, but benefits and costs need not be symmetrically distributed.
- We next model the how the entire conditional distribution of earnings shifts following innovation shocks using quantile regressions

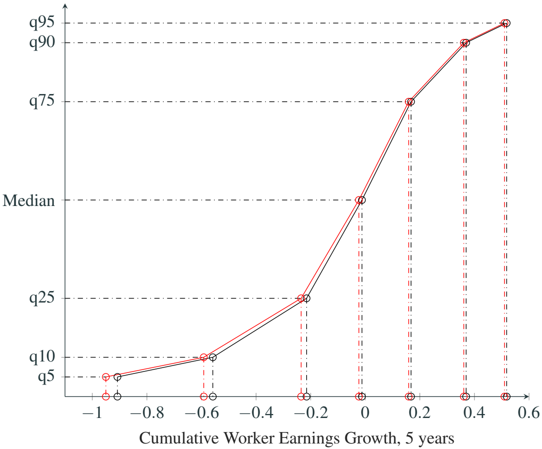


- All marginal effects for own innovation are positive:
  - CDF of income growth rates **shifts to the right** (more upside, no change in downside)

Competitor Innovation

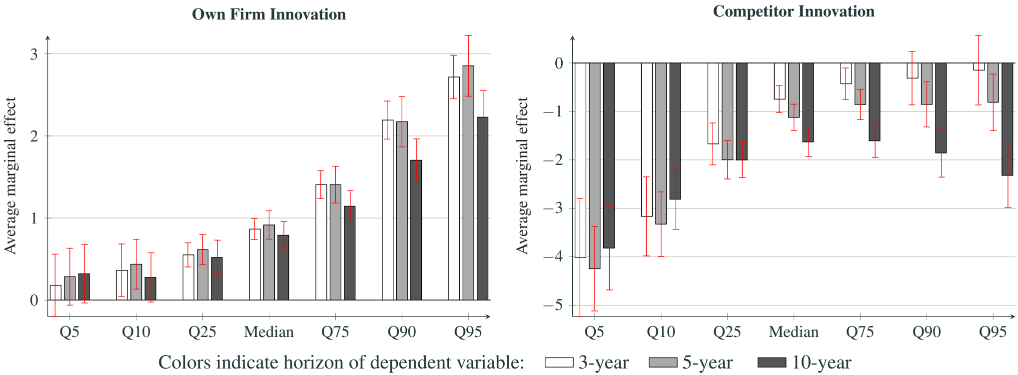


Implied Change in CDF of Earnings Growth



- All marginal effects for competitor innovation are negative:
  - CDF of income growth rates **shifts to the left** (increase in downside, no change in upside)

Effects comparable across horizons

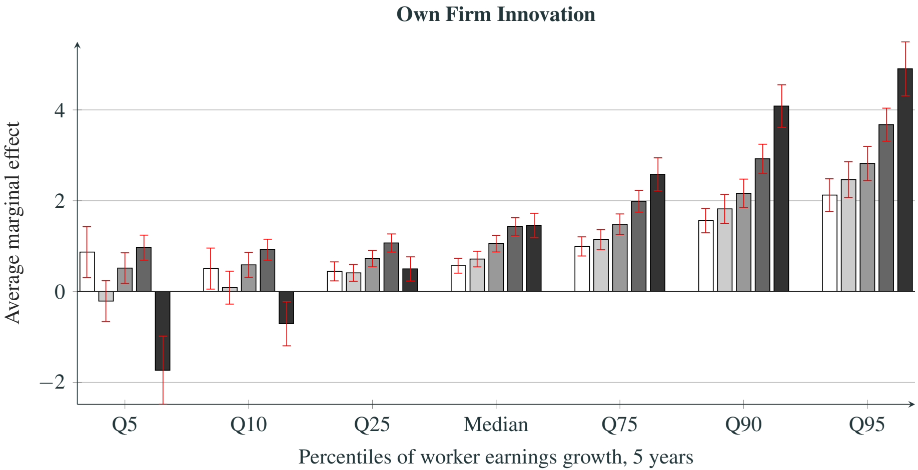


- Effects on worker earnings appear permanent. Magnitudes?
  - A worker with a CRRA $\gamma = 5$ will experience a 3.4% reduction in her CEQ in response to a one-σ shock to innovation by competing firms
  - Comparable to the estimated cost of business cycles due to job displacement (Krebs, 2007)

Thus far...

- Innovation followed by shifts in distribution of worker earnings
  - Own innovation associated with more right-skewed worker earnings.
  - Competitor innovation associated with negatively skewed earnings.
- Ex-post heterogeneity driven by ex-ante differences?
  - Re-estimate allowing key coefficients to vary across observables
- For now, focus on prior income: Rank workers within firm into 5 bins on lagged (life-cycle adjusted) income levels
  - Bins 1-3: bottom three quartiles
  - Bin 4: 75th through 95th percentiles
  - Bin 5: 95th through 100th percentiles

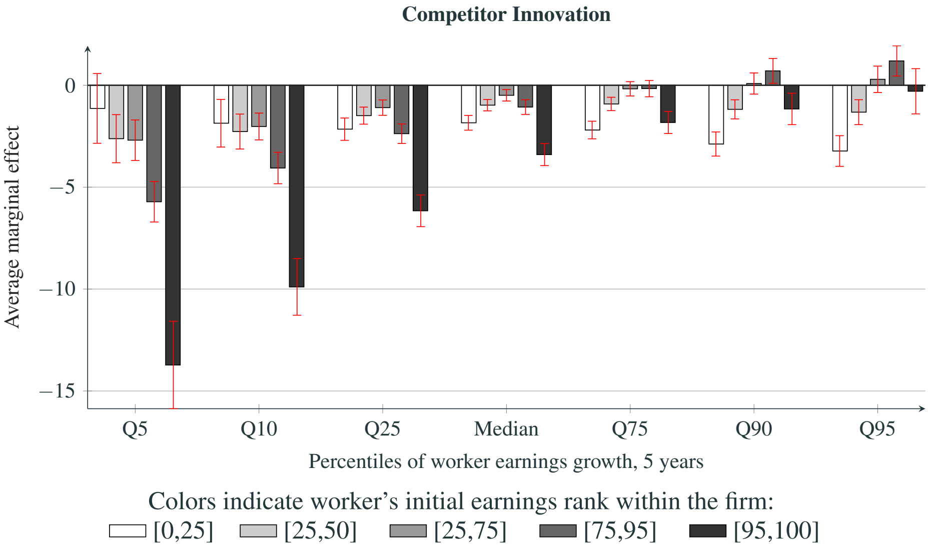
Marginal effects by earnings rank: Own-firm Innovation

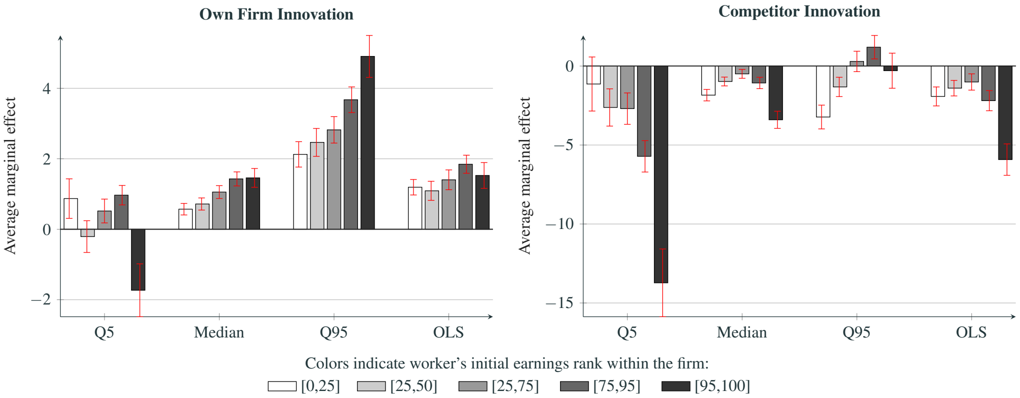


Colors indicate worker's initial earnings rank within the firm:

[0,25] [25,50] [25,75] [75,95] [95,100]

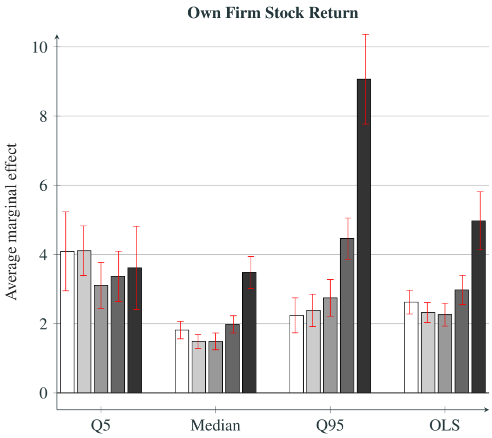
Marginal effects by earnings rank: Competitor Innovation

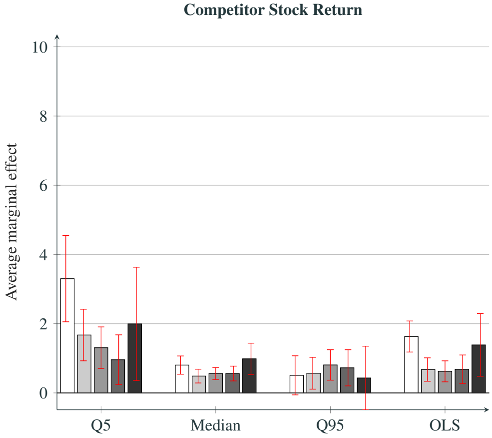




- Top workers have higher exposure to innovation shocks
  - Movements in left tail in response to competitor innovation comparable to difference between expansions–recessions (Guvenen, et al. 2014 Figure 10).
  - A top worker with a CRRA $\gamma = 5$ will experience a 11% reduction in her CEQ in response to a one-σ shock to innovation by competing firms

Contrast: worker earnings responses to stock returns





Colors indicate worker's initial earnings rank within the firm:

[0,25] [25,50] [25,75] [75,95] [95,100]

Understanding the mechanism

- Let us now dig a bit deeper into what drives the increase in the left tail.
- Data allows us to track workers across firms.
- Decompose findings into
  1. Likelihood of leaving the firm $(M = 1)$ following innovation outcomes I
  2. Distribution of future earnings growth g conditional on mobility M

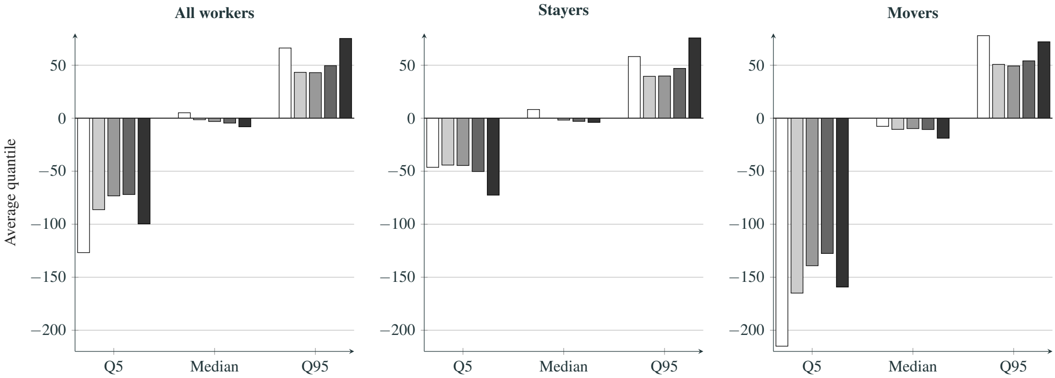
$$f(g|\mathrm{I}) = f(g|\mathrm{I}, M = 1)\, p(M = 1|\mathrm{I}) + f(g|\mathrm{I}, M = 0)\,(1 - p(M = 1|\mathrm{I}))$$

- No role for skill displacement, hence

$$f(g|\mathrm{I}, M) = f(g|M)$$

this obviously need not be the case in the data...

Exiting workers have more left-skewed earnings growth



Stayer $\equiv$ has same main employer at time $t+3$

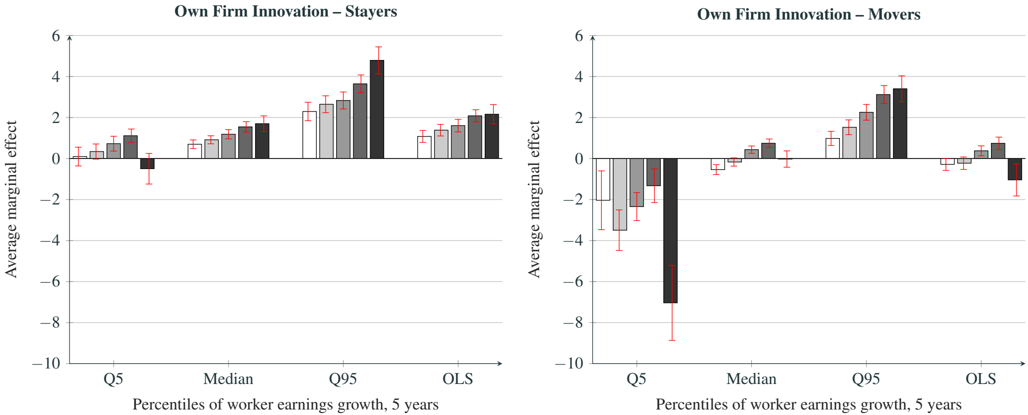
Colors indicate worker's initial earnings rank within the firm:

Probability of leaving the firm

Outcome: Worker leaves the firm within 3 yrs $p(M=1\|I)$					
	Worker earnings rank				
	[0,25]	[25,50]	[50,75]	[75,95]	[95,100]
Innovation by the firm, A_f	-1.91	-1.74	-1.74	-1.70	-1.46
	(-14.65)	(-13.63)	(-13.13)	(-12.80)	(-9.56)
Innovation by competitors, $A_{I\setminus f}$	-1.09	-0.20	0.42	1.11	1.13
	(-4.22)	(-0.79)	(1.67)	(4.33)	(4.03)

Note: Coefficients multiplied by 100; SE clustered by firm

- Baseline probability that a worker leaves the firm after 3 years is 36%
  - High innovation by firm followed by lower rate of separation
  - High innovation by competitors increase exit rate for top half of workers
- But, only part of the story. Next, examine variation in outcomes among exiting workers following innovation outcomes
  - Estimate quantile regressions separately for movers and stayers
  - Obtain estimates of $f(g|I,M)$



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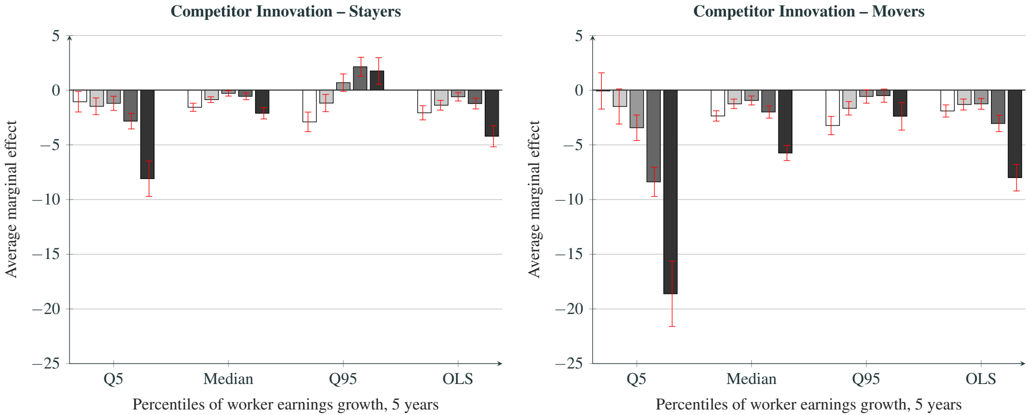

Stayer ≡ has same main employer at time $t+3$

Colors indicate worker's initial earnings rank within the firm:

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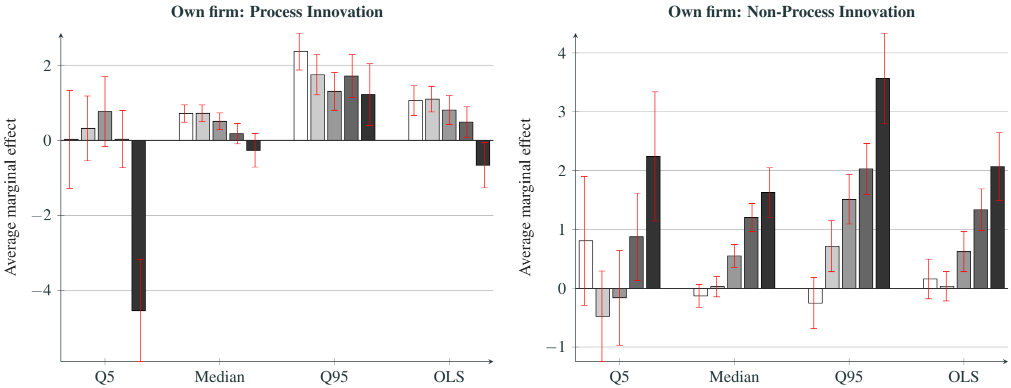
Process vs non-process innovation

- In model, own firm innovation can also displace the firm's own workers
  - worker replaced with probability p
- Replacement more likely in process improvements (vs products)
  - Testable? Text-based classification of Bena and Simintzi (2016)
  - Approximately 30% of all patent claims classified as 'process'
- Focus on innovation by the firm, and decompose A_f into process and non-process: assign corresponding fraction of each patent.
  - Caveat: process and non-process measures highly correlated (approx. 70%) so results will be noisy



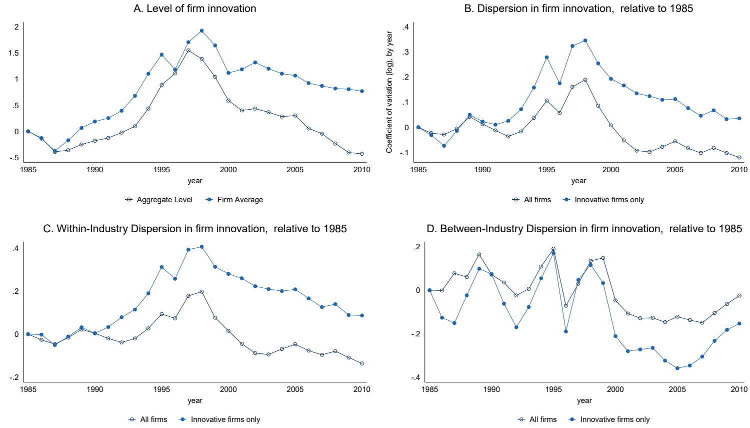
Colors indicate worker's initial earnings rank within the firm:

[0,25] [25,50] [25,75] [75,95] [95,100]

- Own firm 'product' innovation mostly a location shift
- Own firm process innovation → more negatively skewed earnings growth for top workers (estimates even larger for movers)

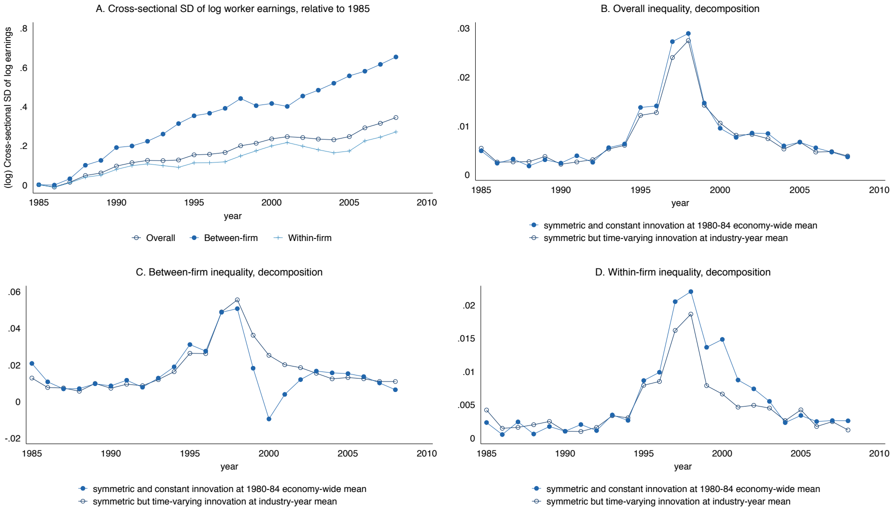
How much did firm innovation contribute to income inequality?

Fact: During the 1990s, both level and dispersion of innovation increased across firms (mostly a within-industry effect)



Quantitative implications for inequality

- Given our point estimates, shifts in the distribution of firm innovation will lead to movements in income inequality across workers, both between as well as within firm.
- We simulate worker earnings from the quantile regression model under three alternatives:
  1. The realized values of firm A_f and competitor $A_{I\setminus f}$ innovation
  2. constant level and dispersion: set A_f and $A_{I\setminus f}$ to 1980–85 (industry) levels
  3. constant dispersion: set A_f and $A_{I\setminus f}$ equal to industry-year mean
- Comparing the time series of inequality between (1) and the two alternatives (2) or (3) quantifies the contribution of the increases in the level or dispersion, of innovation.



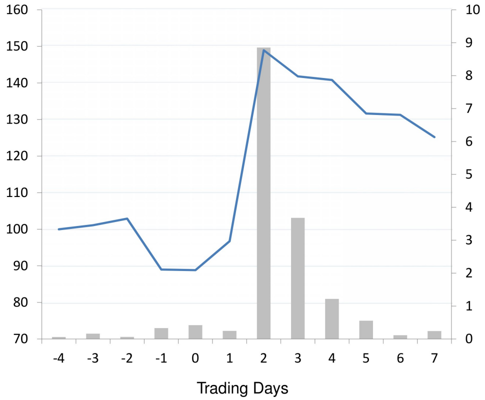
A. Cross-sectional SD of log worker earnings, relative to 1985
(log) Cross-sectional SD of log earnings
.8
.6
.4
.2
0
1985
1990
1995
2000
2005
2010
year
Overall
Between-firm
Within-firm
B. Overall inequality, decomposition
.03
.02
.01
0
year
symmetric and constant innovation at 1980-84 economy-wide mean
symmetric but time-varying innovation at industry-year mean
C. Between-firm inequality, decomposition
.06
.04
.02
0
-.02
year
symmetric and constant innovation at 1980-84 economy-wide mean
symmetric but time-varying innovation at industry-year mean
D. Within-firm inequality, decomposition
.02
.015
.01
.005
0
year
symmetric and constant innovation at 1980-84 economy-wide mean
symmetric but time-varying innovation at industry-year mean

Summary and Conclusion

- Innovation associated with considerable labor income risk
  - Workers bear a larger share of the costs of innovation than the benefits
- Creative destruction followed by increase in left tail of labor income
  - Effects stronger for top workers
  - Effects mainly driven by separations
  - Own-firm displacement effects driven by process innovations
- Concentration of innovation outcomes in a small set of firms in the 1990s also accounts for significant increase in between-firm inequality

APPENDIX

Stock market and patent issues



- **Stock price (left axis) and trading volume (right axis) of GENEX Co on August 7, 1990, after award of patent no. 4,946,778 for "Single-Chain Polypeptide Binding Molecules"**

Share turnover during patent issuance weeks

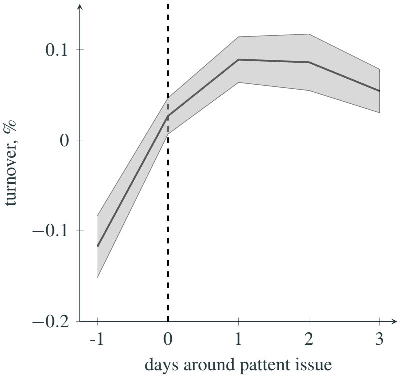
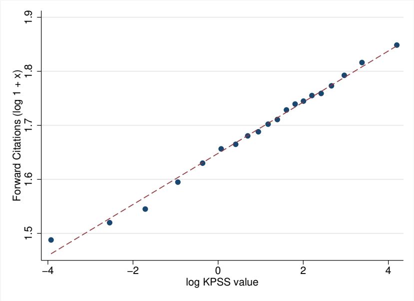


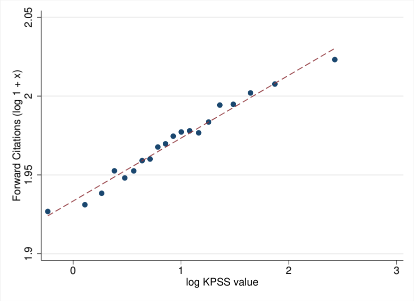
Figure plots the share turnover around patent issuance days. Share turnover h is the ratio of daily volume (CRSP: vol) to shares outstanding (CRSP: shrout). The median daily share turnover is 1.29%. We report the coefficient estimates b_l, $l = -1 \ldots 3$, (and 90% confidence intervals) from the following specification:

$$h_{fd} = a_0 + \sum b_l I_{fd+l} + c Z_{fd} + \varepsilon_{fd},$$

Forward citations and patent market value



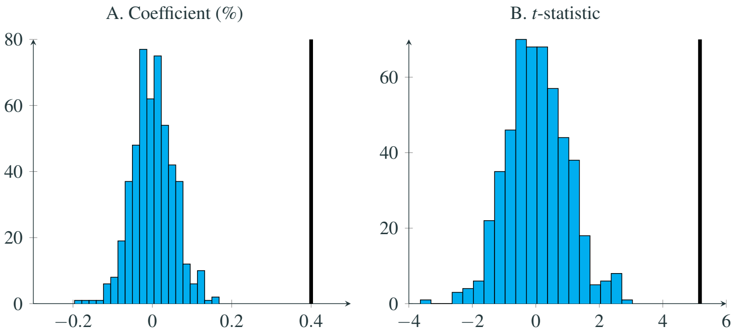
Issue year controls



Issue year, Tech class, Firm Char, Firm FE controls

Figure plots the cross-sectional relation between forward patent citations and the estimated market value of patents. We group the patent data into 100 quantiles based on their cohort adjusted citations $(1 + C/\bar{C})$. The horizontal axis plots the log of average cohort adjusted patent citations in each quantile. The vertical axis plots the logarithm of the average patent value in each quantile (scaled by the average value of patents granted in the same year). Back

Relation between stock market reaction and number of citations across placebo experiments



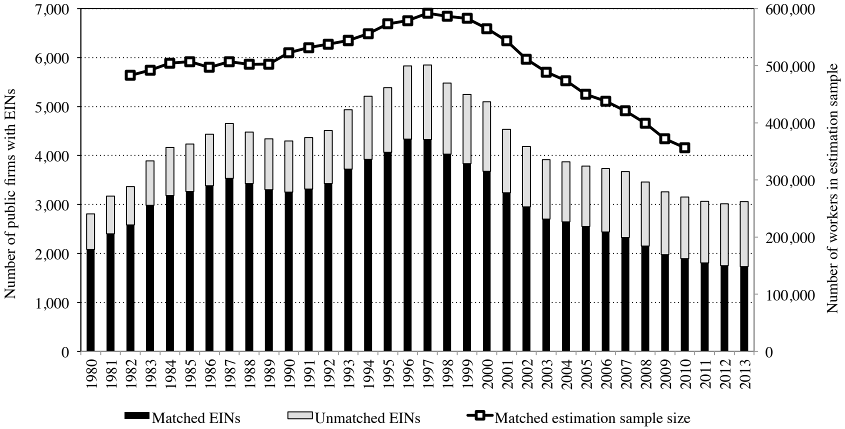
Note: Figure plots distribution of estimated coefficients $\hat{b}$ (panel A) and t-statistics (panel B), from estimating equation linking forward citations and estimated patent values (with full set of controls) across 500 placebo experiments. In each placebo experiment, we randomly generate a different issue date for each patent within the same year the patent is granted to the firm. We then reconstruct our measure using these placebo grant dates. The solid line on the right corresponds to the

Interpreting the dependent variable

- Sum over multiple years for two reasons:
  1. mitigate problem with observations with zero income when using year-on-year growth rates
  2. smooths large changes in earnings that may be induced by large transitory shocks $\rightarrow$ more emphasis on persistent earnings
- To see 2, suppose that annual log income (net of age effects) is sum of:
  - permanent random walk component: $\xi_{i,t} = \xi_{i,t-1} + \eta_{i,t}$
  - iid, mean zero, transitory component: $\varepsilon_{i,t}$
- A log-linear approximation of $Y_{i,t:t+5}$ around zero is:

$$
\begin{aligned}
Y_{i,t:t+5} \quad \approx \quad & \frac{1}{5}\eta_{i,t+5} + \frac{2}{5}\eta_{i,t+4} + \frac{3}{5}\eta_{i,t+3} + \frac{4}{5}\eta_{i,t+2} + \eta_{i,t+1} + \frac{2}{3}\eta_{i,t} + \frac{1}{3}\eta_{i,t-1} \\
+ \quad & \frac{1}{5}\left[\varepsilon_{i,t+5} + \varepsilon_{i,t+4} + \varepsilon_{i,t+3} + \varepsilon_{i,t+2} + \varepsilon_{i,t+1}\right] - \frac{1}{3}\left[\varepsilon_{i,t} + \varepsilon_{i,t-1} + \varepsilon_{i,t-2}\right].
\end{aligned}
$$

Characteristics of the matched sample



- Exclude financials and utilities ⇒ 11.4 million matched observations
- Matching rates are roughly constant across major SIC industries

Firm-level summary stats

Table 2: Firm descriptive statistics: matched vs non-matched sample

	Obs	Mean	SD	1%	5%	10%	25%	50%	75%	90%	95%	99%
A. Matched sample												
Employment ('1000s)	101,980	6.64	29.04	0.01	0.02	0.05	0.15	0.64	3.15	12.50	28.30	108.00
Employment (SSA, '1000s)	104,071	2.52	12.14	0.00	0.01	0.01	0.06	0.23	1.03	4.19	9.93	42.23
Book assets, log	104,068	4.66	2.14	0.42	1.34	1.94	3.14	4.52	6.07	7.57	8.45	10.02
RD to assets	65,217	0.10	0.15	0.00	0.00	0.00	0.01	0.05	0.12	0.24	0.38	0.77
ROA	103,703	-0.02	0.29	-1.31	-0.58	-0.30	-0.02	0.07	0.12	0.17	0.20	0.29
Firm Innovation	104,068	0.05	0.16	0.00	0.00	0.00	0.00	0.00	0.01	0.12	0.27	0.80
Firm innovation, process	104,068	0.02	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.09	0.30
Firm innovation, non-process	104,068	0.03	0.10	0.00	0.00	0.00	0.00	0.00	0.01	0.07	0.16	0.46
B. Non-Matched sample												
	Obs	Mean	SD	1%	5%	10%	25%	50%	75%	90%	95%	99%
Employment ('1000s)	37,397	9.52	46.51	0.00	0.01	0.04	0.19	1.10	4.90	18.80	41.00	133.00
Book assets, log	38,663	5.33	2.25	0.59	1.62	2.30	3.71	5.34	6.93	8.27	9.10	10.40
RD to assets	18,712	0.07	0.13	0.00	0.00	0.00	0.00	0.02	0.07	0.18	0.29	0.68
ROA	38,433	0.00	0.26	-1.25	-0.47	-0.21	0.00	0.07	0.12	0.17	0.21	0.30
Firm Innovation	38,663	0.02	0.11	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.12	0.54
Firm innovation, process	38,663	0.01	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.04	0.24
Firm innovation, non-process	38,663	0.01	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.14

Note: Table reports univariate summary statistics for the sample of matched (Panel A) and unmatched (Panel B) public firms. The unit of analysis is the GVKEY-year.

Worker-level summary stats

Table 1: Worker descriptive statistics: Full versus matched sample

	Obs	Mean	SD	1%	5%	10%	25%	50%	75%	90%	95%	99%
Panel A. Matched sample												
Wage (in 2013 dollars)	14,621,600	74,199	146,577	4,826	15,855	24,321	39,273	57,577	82,765	123,248	165,383	343,534
Age	14,621,600	39.6	8.0	26.0	27.0	29.0	33.0	39.0	46.0	51.0	53.0	54.0
Firm tenure	14,621,600	6.2	5.2	1.0	1.0	1.0	2.0	5.0	9.0	14.0	17.0	23.0
Firm tenure $\geq$ 3 years	14,621,600	0.7	0.4	0.0	0.0	0.0	0.0	1.0	1.0	1.0	1.0	1.0
Cumulative 3-year wage growth	14,593,617	-0.07	0.59	-2.31	-0.88	-0.53	-0.17	-0.01	0.13	0.38	0.58	1.10
Left firm after 1 year	14,621,600	0.15	0.36	0	0	0	0	0	0	1	1	1
Left firm after 3 year	14,621,600	0.34	0.47	0	0	0	0	0	1	1	1	1
Panel B. SSA worker sample (based on 10% sample)												
	Obs	Mean	SD	1%	5%	10%	25%	50%	75%	90%	95%	99%
Wage (in 2013 dollars)	110,927,670	58,190	121,135	2,729	7,836	13,803	26,471	43,366	65,982	100,271	138,168	313,623
Age	103,635,050	38.9	8.1	26.0	27.0	28.0	32.0	39.0	46.0	51.0	52.0	54.0
Firm tenure	110,762,520	5.1	4.7	1.0	1.0	1.0	2.0	3.0	7.0	12.0	15.0	21.0
Firm tenure $\geq$ 3 years	110,762,520	0.6	0.5	0.0	0.0	0.0	0.0	1.0	1.0	1.0	1.0	1.0
Cumulative 3-year wage growth	103,635,050	-0.09	0.65	-2.63	-1.08	-0.64	-0.21	-0.01	0.15	0.43	0.66	1.26
Left firm after 1 year	110,540,010	0.25	0.43	0	0	0	0	0	0	1	1	1
Left firm after 3 year	110,016,540	0.45	0.50	0	0	0	0	0	1	1	1	1

Note: Table reports univariate summary statistics for the sample of matched (Panel A) and unmatched (Panel B) worker-level measures. The unit of analysis is the SSN-year.

- Manufacturing workers over-represented (exclude industries w/o patents)

Statistical framework: model for multiple quantiles

- Estimate a parametric model for the 5th, 10th, 25th, 50th, 75th, 90th, and 95th percentiles of $Y_{i,t:t+h}$. Allows conditional quantiles to vary depending on innovation + firm, individual, industry, and time coefficients.
- Use a method from Schmidt and Zhu (2016) to estimate the model:

$$q_j(x) = \begin{cases} x'\beta_0 & \text{if } j = j^* \\ x'\beta_0 - \sum_{k=j}^{j^*-1} \exp(x'\beta_k) & \text{if } j < j^* \\ x'\beta_0 + \sum_{k=j^*+1}^{j} \exp(x'\beta_{k-1}) & \text{if } j > j^* \end{cases},$$

  where j indexes the seven quantiles of interest and $j^* = 4$ (the median)
- Can also estimate average marginal effects:

$$E\left[\frac{\partial q_j(X_{i,t})}{\partial X_{i,t}}\right] = \begin{cases} \beta_0 & \text{if } j = j^* \\ \beta_0 - \sum_{k=j}^{j^*-1} E[\exp(X'_{i,t}\beta_k)]\beta_k & \text{if } j < j^* \\ \beta_0 + \sum_{k=j^*+1}^{j} E[\exp(X'_{i,t}\beta_{k-1})]\beta_k & \text{if } j > j^* \end{cases}.$$

Comparison: expansions vs recessions (GOS, 2014)

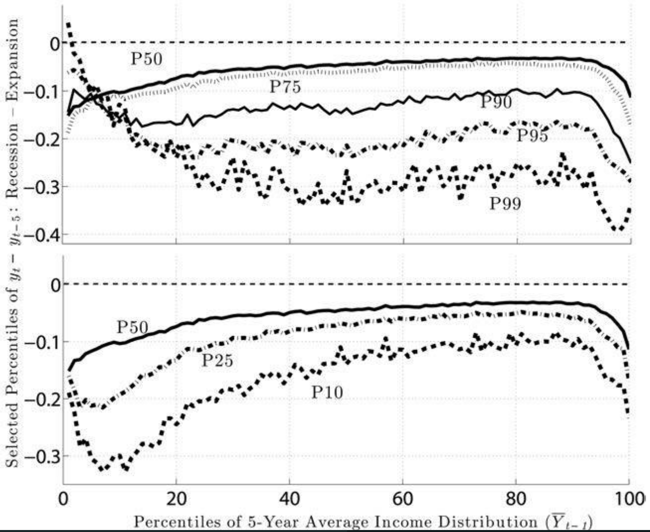


Figure A.2: Innovation and growth - Firm-level outcomes across horizons, varying timing conventions

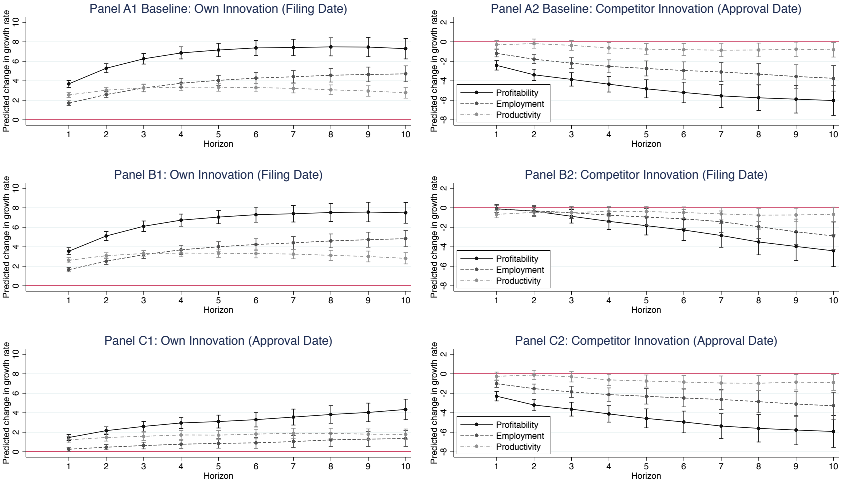


Figure A.3: Firm stock returns and innovation: movers versus continuing workers

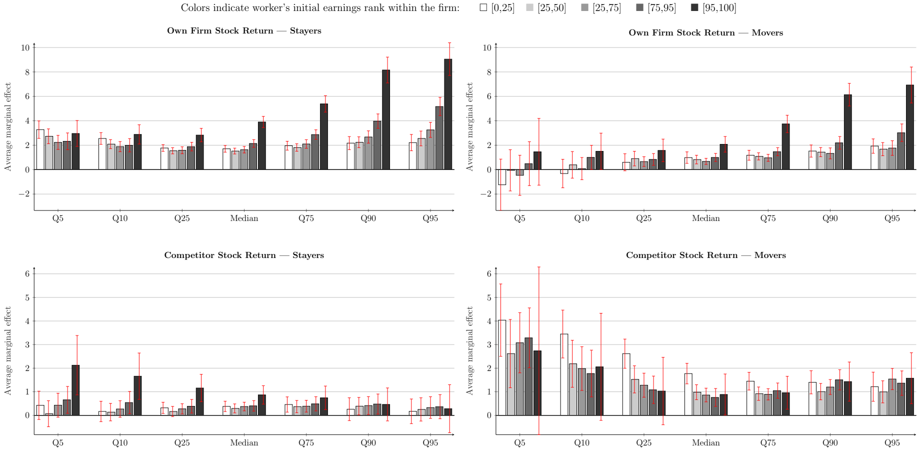


Figure A.4: Earnings growth and innovation conditional on age and earnings levels

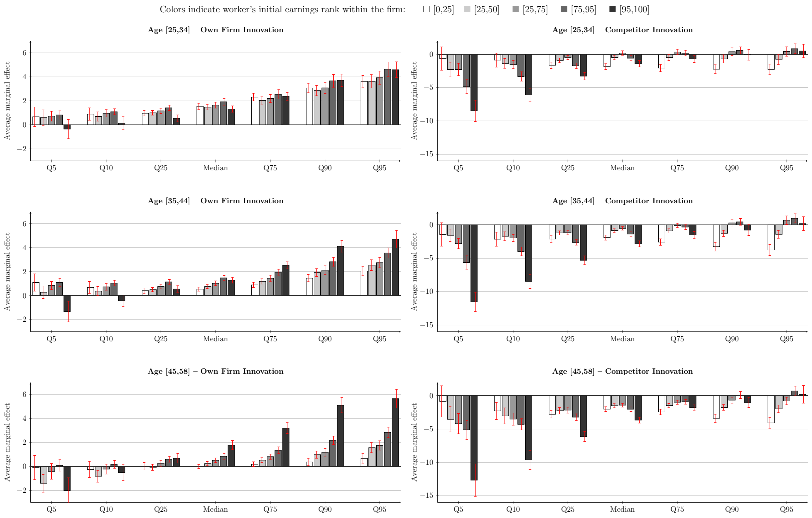


Figure A.5: Unconditional quantiles versus average fitted quantiles by firm rank bin

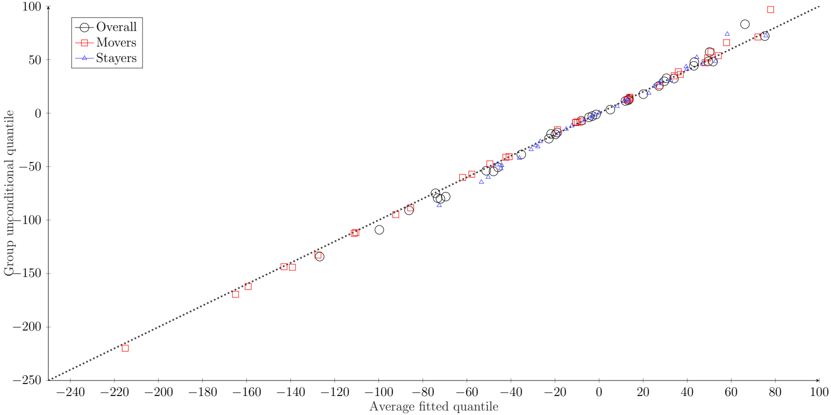
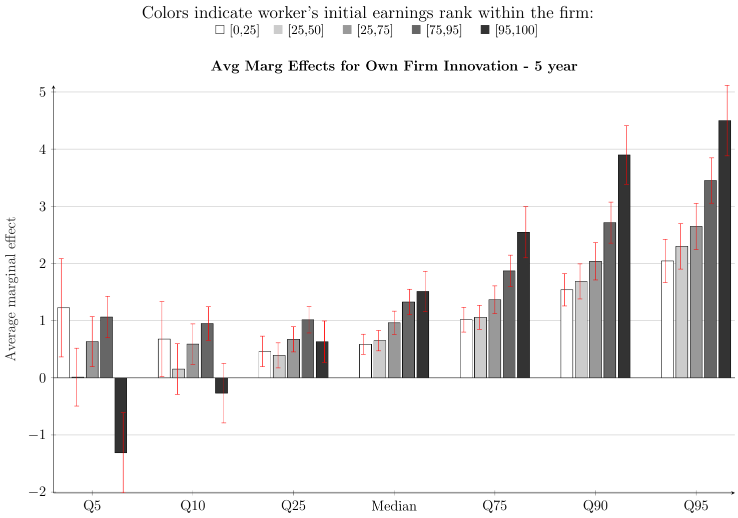


Figure A.7: Earnings growth and innovation conditional on earnings levels - control for R&D spending



Avg Marg Effects for Competitor Innovation - 5 year

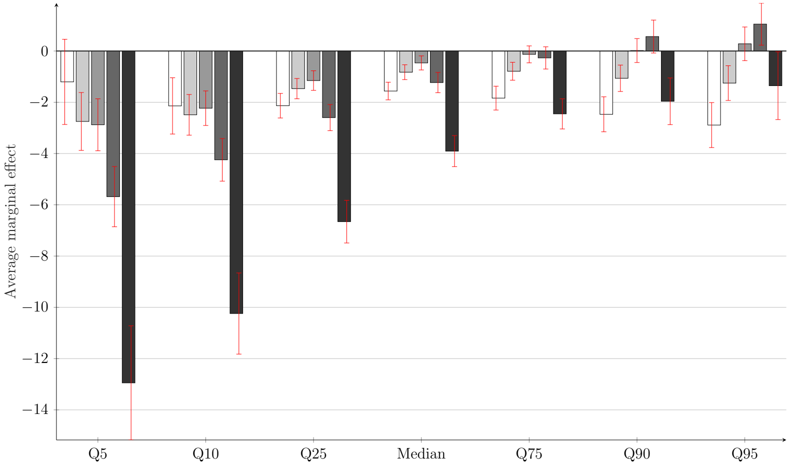
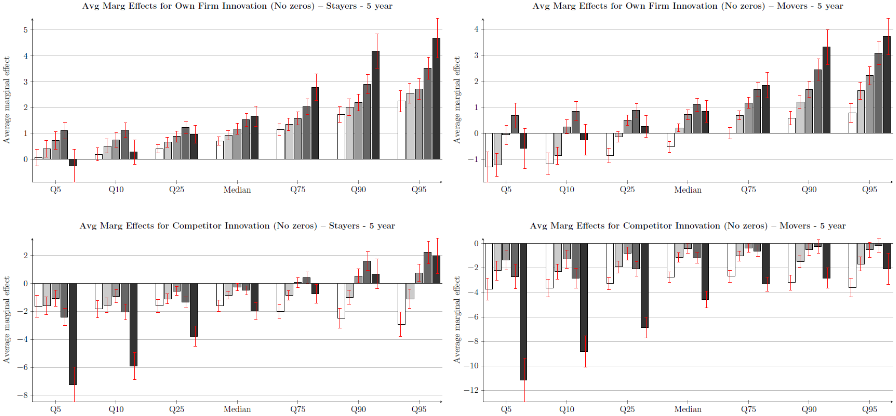
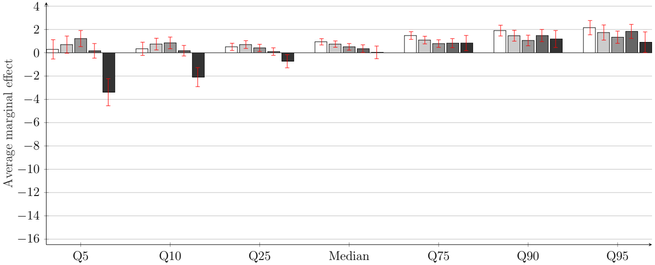


Figure A.8: Earnings growth and innovation: movers versus continuing workers - exclude years with zero income obs

Colors indicate worker's initial earnings rank within the firm: [0,25] [25,50] [25,75] [75,95] [95,100]



C. Own Firm: Process Innovation — Stayers



D. Own Firm: Process Innovation — Movers