A Analytical Derivations

Here, we briefly describe the derivation of the model. The demand for variety i can be obtained from the optimization problem of the final-goods producer

$$\max_{\{x_{i,t}\}} \left(\int_0^1 x_{i,t}^{\nu} \right) - \int_0^1 p_{i,t}\, x_{i,t}, \tag{A.1}$$

which yields the inverse demand curve as the first-order condition for good i,

$$\begin{aligned} p_{i,t} &= \nu\, x_{i,t}^{\nu-1}. \\ \left(\frac{p_{i,t}}{\nu}\right)^{\frac{1}{\nu-1}} &= x_{i,t} \end{aligned} \tag{A.2}$$

Next, consider the problem faced by the leading producer of good i. She can set a price such that the firm with the next-best level of efficiency–denoted by q'–finds it unprofitable to produce. That is, she sets a limit price equal to the second-best producer's marginal cost,

$$p_{i,t} = \frac{W_t}{q'_{i,t}}, \tag{A.3}$$

where W is the marginal cost of employing the fixed factor l. Hence, the leading firm produces an amount equal to

$$\left(\frac{W_t}{\nu q'_{i,t}}\right)^{\frac{1}{\nu-1}} = x_{i,t}. \tag{A.4}$$

Hence, the flow profits to the leading producer are equal to

$$\begin{aligned} \Pi_{i,t} &= \left(p_{i,t} - \frac{W_t}{q_{i,t}}\right) x_{i,t} \\ &= (\kappa - 1) \left(\frac{\kappa}{\nu}\right)^{\frac{1}{\nu-1}} \left(\frac{q_{i,t}}{W_t}\right)^{\frac{\nu}{1-\nu}}, \end{aligned} \tag{A.5}$$

where $\kappa \equiv q_{i,t}/q'_{i,t} > 1$ is the efficiency gap. These profits include the payment to the skilled worker/manager. Since she can only steal a fraction β if she diverts one unit of output, the solution to this contracting problem is to give her a fraction β of the profits, in which case she is indifferent between stealing versus not. Last, market clearing determines W_t

$$\begin{aligned} 1 &= \int_0^1 l_{i,t}\, di \\ W_t &= \frac{\nu}{\kappa} \left[\int_0^1 q_{i,t}^{\frac{\nu}{1-\nu}}\, di \right]^{1-\nu}. \end{aligned} \tag{A.6}$$

B Data Appendix

Here, we describe our data construction in more detail.

B.1 SSA administrative earnings records

For our empirical analysis, we work with a 10% random sample of confidential, panel earnings records for males which is drawn from the U.S. Social Security Administration (SSA)'s Master Earnings File (MEF). The MEF includes annual earnings information which is top-coded at the SSA annual contribution limit prior to 1978, and uncapped information on annual earnings from 1978-2013. Due to several potential measurement issues in the initial years following the transition to uncapped earnings, we start our analysis in 1980 (see, e.g., Guvenen et al., 2014, for further details).

Our main sample selection criteria and variable construction methods, unless otherwise stated, closely follow Guvenen et al. (2014). Specifically, we exclude the self-employed and exclude worker-years for individuals who have not had at least three out of the prior five years of earnings exceeding a minimum threshold. The minimum earnings threshold is the amount one would earn working 20 hours per week for 13 weeks at the federal minimum wage. For an individual worker to appear in the sample at time t, we require that she not receive self-employment earnings in excess of 10% of total wage income or the above minimum earnings threshold in any of the years which are used to construct either conditioning or dependent variables. All earnings are converted to 2010 dollars using the personal consumption expenditure deflator. We restrict attention to workers who are above the age of 25 at time t, and, when we calculate growth rates, we require that the worker has at least one year with earnings above the threshold during which he is below the age of 60. Even after applying these filters, the sample includes over 100 million worker-year observations.

In addition to total annual earnings, the MEF also includes detail on the Employer Identification Number (EIN) and SIC codes of the three employers which were associated with the highest annual earnings for each individual. This information allows us to link each worker-year earnings measure with a particular firm and industry, and also to detect when workers switch employers. When an individual receives income from more than one job in a given year, we associate her with the EIN of the firm that pays the highest total wage, following Autor et al. (2014) and Song et al. (2019).

Using this mapping between workers and EINs, we also construct measures of an individual's tenure within the firm, which is the number of consecutive years for which the firm has been the worker's largest source of W-2 income. In addition, we construct measures of switches between firms. For instance, we can compute the probability that a worker who is currently employed at firm j at time t continues to be employed at the firm at time $t + h$.

Following Guvenen et al. (2014), we estimate age dummy coefficients by regressing log wages on age and cohort-specific effects in a random 10% sample of the data. We choose 25 year old as the omitted base category, so the age dummy captures the average ratio of the log wage of an older worker to a 25 year old over the sample period. $D(\text{age}_{i,t})$ is obtained by exponentiating the age dummies. At the very start of a worker's income record, we only divide by dummy variables associated with years after his first W-2 record above the minimum earnings threshold. For example, if a worker who is 25 at time t had his first W-2 record above the minimum threshold in time $t - 2$, then we only divide through by $\sum_{j=0}^{2} D(age_{i,t-j})$.

In addition to total annual earnings, the MEF also includes detail on the Employer Identification Number (EIN) of the three employers which were associated with the highest annual earnings for each individual. This information allows us to link each worker-year earnings measure with a particular firm and industry, and also to detect when workers switch employers. Using this mapping between workers and EINs, we also construct measures of an individual's tenure within the firm, which is the number of consecutive years for which the firm has been the worker's largest source of W-2 income.

B.2 Constructing a Matched Sample of Public Firms

Next, we use the EIN numbers in the MEF to map the innovation measures–which are only available for public firms–with individual workers' earnings histories and to get a richer picture of how the conditional distribution of workers' income growth rates change with innovative output. For instance, the EIN appears directly below the legal company name on the cover page of the annual (10-K) and quarterly (10-Q) financial statements. Following standard practice, we exclude from the analysis financial firms (SIC codes 6000-6799) and utilities (SIC codes 4900-4949), as well as firms for which cannot find EINs, which leaves us with a sample of around 142 thousand firm-years over the 1980-2013 period. While SIC code information is available in the MEF, we use the SIC code information from their financial statements for our analysis.

We combine two data sources in order to match the firm identifier (GVKEY) from CRSP-Compustat Merged (CCM) database to EINs to the MEF. First and foremost, EIN numbers of publicly traded firms are readily available in their SEC filings, appearing on the front page of each firm's annual report (form 10-K). We can access both current and historical EIN information from the company header files, which gives us a set of EINs which are associated with a given firm. In a small number of cases, the same EIN can be associated with multiple firm identifiers (GVKEYs). In the vast majority of cases, only one of the two records is active over a given date range, or one of the two filers is a subsidiary of the other. In the latter case, we associate the EIN with the GVKEY of the parent firm. In the small remainder of cases, we only keep the GVKEY-EIN mapping from the current header file. However, the EIN from the 10-K may only be picking up a subset of the total employee base for each of these firms, because many firms pay workers through multiple EINs. For instance, Song et al. (2019) report that, according to Dun & Bradstreet data, the average firm listed on the New York Stock Exchange is associated with 3.2 EINs. To this end, the gap between the employment measure from firms' 10-K (which also includes employment in other countries and subsidiaries) and the number of W-2's in the MEF tends to be largest in percentage terms for the firms with the highest reported 10-K employment.

To improve our coverage of employment at firms with multiple EINs, we bring in an additional source of information. We augment our existing list of GVKEY-EIN links with information from firms' form 5500 filings, which are publicly-available documents that report information about firms' benefit plans to comply with the Employee Retirement Income Security Act (ERISA).[22] This dataset provides a link between company identifying information (name, address, etc.) and EINs, and includes approximately 600 thousand unique EIN numbers per year starting in 1999. Prior to 1999, filings by firm plans with fewer than 100 participants are not included in the FOIA data, so sample sizes are smaller. We can then link company names on form 5500 to a list of "major subsidiaries" in Exhibit 21 which each firm is required to file on its annual report. Combining these two sources allows us to associate a given GVKEY with additional EINs of firm subsidiaries and/or other EINs associated with parent firms' retirement plans. We are extremely grateful to Josh Rauh and Irina Stefanescu for sharing a link file between the form 5500 data and CCM data which was used in Rauh and Stefanescu (2009) and Rauh, Stefanescu, and Zeldes (2019), which we used as a starting point for the empirical analysis.

Incorporating subsidiary information increases the size of our estimation sample by about 50%, from 7.8 million to 11.4 million worker-years in our baseline estimation. However, we do note that our main results appear unchanged if restrict the sample to using the EIN numbers from the current header file only, which corresponds with the EIN a firm's most recent 10-K.

[22] We access FOIA information for filings from 1999-present from the US Department of Labor's website: `https://www.dol.gov/agencies/ebsa/about-ebsa/our-activities/public-disclosure/foia/form-5500-datasets`. Information from 1990-1998 is taken from the Center for Retirement Research at Boston College University: `http://crr.bc.edu/data/form-5500-annual-reports/`.

Figure A.1, panel A, shows the number of public firms with EINs which are matched and unmatched to W-2 records in the MEF by year. On average, matching rates are quite high. We can find records in the MEF for about 84% of the public firm-years. That said, there is a core group of around 650 firms that we cannot find per year, which causes overall matching rates decline to some extent post-2000 due to a gradual decline in the total number of public firms. Figure A.1, panel B, shows the number of matched and unmatched firms by major SIC industry group. We observe that the industry composition of the two samples are broadly similar.

Table A.1 provides summary statistics for observations which meet our screening criteria for being included in the estimation for the full sample and matched sample, respectively. We note that employees at public firms are slightly older and earn about $16 thousand dollars more per year. Workers at matched public firms have about a year of additional tenure on average, and are also more likely to have tenure greater than or equal to 3 years relative to workers at non-matched firms. Recall from our earlier discussion that the tenure measure is censored by the fact that our sample starts in 1980; therefore, these summary statistics provide a lower bound on the population distribution of firm tenure. For this reason, our empirical specifications involving tenure will emphasize a binary measure which is not subject to this downward bias.

Table A.3 compares the characteristics of matched and unmatched firms over our sample period. Matched firms tend to be similar in terms of book assets, but larger in terms of employment (as reported on 10-K forms). Given the discussion above about the fact that some firms may have multiple EINs associated with different divisions and/or subsidiaries, such a result is to be expected. Matched firms are also somewhat more innovative. The ratio of R&D to assets, as well as average values of each of our three innovation measures–which we will describe in the next section–are all higher for the sample of matched firms. For the sample of matched firms, we can also compute a measure of total employment from the SSA data by counting up the total number of W-2's associated with each employer. The average firm in our matched sample has about 3,800 employees according to this measure. On average, the SSA-implied employment measure is smaller than the number reported in firms' financial statements. This result is unsurprising given that the 10-K number is more inclusive and the fact that some firms may pay employees through multiple EINs, not all of which are found in the 5500 data.

B.3 Cumulative Earnings Growth and Transitory Shocks

When focusing on income changes, our main variable of interest will be the growth in age-adjusted income $w^i_{t,t+k}$ over a horizon of h years, defined as follows:

$$Y_{i,t:t+h} \equiv w^i_{t,t+h} - w^i_{t-2,t}. \tag{A.7}$$

Here, we have chosen as our baseline the average (age-adjusted) earnings between $t-2$ and t as the scaling factor; that said, our results are similar if we extent the window to 5 years. Focusing on the growth of average income over multiple horizons in (A.7) has two distinct advantages. First, summing over multiple years yields a much smaller number of observations with zero income relative to a simple comparison of year-on-year income changes. Second, and more importantly, this transformation can smooth out some large changes in earnings that may be induced by large transitory shocks, which places a higher emphasis on persistent earnings changes. See Appendix B.3 for more details.

To see the second point more clearly, suppose that annual log income, net of age effects, is the sum of a random walk component $\xi_{i,t} = \xi_{i,t-1} + \eta_{i,t}$ plus an i.i.d transitory component $\varepsilon_{i,t}$. In our benchmark specifications, we set $h = 5$; in this case, a log-linear approximation of our five year earnings measure $Y_{i,t:t+h}$ around zero is:

$$\begin{aligned} Y_{i,t:t+5} &\approx \frac{1}{5}\eta_{i,t+5} + \frac{2}{5}\eta_{i,t+4} + \frac{3}{5}\eta_{i,t+3} + \frac{4}{5}\eta_{i,t+2} + \eta_{i,t+1} + \frac{2}{3}\eta_{i,t} + \frac{1}{3}\eta_{i,t-1} \\ &+ \frac{1}{5}\left[\varepsilon_{i,t+5} + \varepsilon_{i,t+4} + \varepsilon_{i,t+3} + \varepsilon_{i,t+2} + \varepsilon_{i,t+1}\right] - \frac{1}{3}[\varepsilon_{i,t} + \varepsilon_{i,t-1} + \varepsilon_{i,t-2}]. \end{aligned} \tag{A.8}$$

That is, our transformation implicitly computes a weighted average over permanent and transitory shocks of different periods. Our measure places a larger weight on the short-term permanent shocks (e.g., on η_{t+1}) than in the long-term shocks (e.g., at η_{t+5}). More importantly, however, the transitory shocks ε receive mostly a lower weight than the permanent shocks η, hence reducing their importance. Last, given that our measure essentially is an equal-weighted average over the transitory shocks, it is likely to be closer to a normal distribution if the underlying ε shocks are non-normally distributed.

B.4 Measuring Innovation

Here, we summarize the main steps behind the construction of the innovation measure, and refer the reader to Kogan et al. (2017) for additional details.

The Kogan et al. (2017) estimate of the economic value of patent j equals the estimate of the stock return due to the value of the patent times the market capitalization M of the firm that is issued patent j on the day prior to the announcement of the patent issuance:

$$\xi_j = (1 - \bar{\pi})^{-1} \frac{1}{N_j} E[v_j | r_j] \; M_j. \tag{A.9}$$

An important step in this construction is the estimation of the conditional expectation $E[v_j|r_j]$. Kogan et al. (2017) allow for the possibility that the stock price of innovating firms may fluctuate during the announcement window for reasons unrelated to innovation, and hence include an adjustment for measurement error that requires parametric assumptions. We follow their methodology closely. Next, part of the value of the patent may already be incorporated into the stock price, hence (A.9) includes an adjustment that is a function of the unconditional probability $\bar{\pi}$ of a successful patent application—which is approximately 56% in the 1991-2001 period (see, e.g., Carley, Hegde, and Marco, 2014). Since this adjustment does not vary by patent, it has no impact on our analysis. Last, if multiple patents N_j are issued to the same firm on the same day as patent j, we assign each patent a fraction $1/N_j$ of the total value.

The next step involves aggregating (A.9) at the firm and industry level. To construct the measure at the firm level, we sum up all the values of patents $j \in P_{f,t}$ that were granted to firm f in calendar year t,

$$\xi^{sm}_{f,t} = \sum_{j \in P_{f,t}} \xi_j. \tag{A.10}$$

In addition to the measures of innovation based on stock market reactions (A.10), we also construct a measure that weigh patents by their forward citations. Specifically, we measure the amount of innovation by firm f in year t as

$$\xi^{cw}_{f,t} = \sum_{j \in P_{f,t}} \frac{1 + C_j}{1 + \bar{C}_j}, \tag{A.11}$$

where $\bar{C}_j$ is the average number of forward citations received by the patents that belong in the same technology class (as measured by 3-digit CPC codes) and were granted in the same year as patent j. This scaling is used to adjust for citation truncation lags (Hall et al. (2005)) as well as differences in citation patents across technology classes. Both (A.10) and (A.11) are essentially weighted patent counts; if firm f files no patents in year t, both variables are equal zero.

Large firms tend to file more patents. As a result, both measures of innovation above are strongly increasing in firm size (Kogan et al., 2017). To ensure that fluctuations in size are not driving the variation in innovative output, we scale the measure above by firm size. We use book assets as our baseline case,

$$A^k_{f,t} = \frac{\xi^k_{f,t}}{B_{ft}}, \qquad k \in \{sm, cw\}. \tag{A.12}$$

We note that our main results are not sensitive to using book assets for normalization since we also control for various measures of firm size in all our specifications. Our main results are similar if we scale by the firm's market capitalization instead.

We also construct a measure of innovation by competing firms. We define the set of competing firms as all firms in the same industry – defined at the SIC3 level– excluding firm f. We denote this set by $I \setminus f$. We then measure innovation by competitors of firm f as the weighted average of the innovative output of its competitors,

$$A^k_{I\setminus f,t} = \frac{\sum_{f' \in I\setminus f} \xi^k_{f',t}}{\sum_{f' \in I\setminus f} B_{f't}}, \qquad k \in \{sm, cw\}. \tag{A.13}$$

To decompose the total value of innovation into these two types, we rely on the data and classification procedure of Bena and Simintzi (2019). Bena and Simintzi (2019) use text-based analysis to identify patent claims that refer to process innovation. In particular, they identify claims as process innovations as those which begin with "A method for" or "A process for" (or minor variations of these two strings) followed by a verb (typically in gerund form), which directs to actions that are to take place as part of the process. Hence, once can identify the fraction θ_j of claims of patent j that can be identified with a process. The residual claims $1 - \theta_j$ can refer to either types of innovations, for example, new products. We use these fractions to decompose the private value measure A_f into process and non-process innovations; Appendix B.4 contains more details.

To construct $A^{proc}_{f,t}$ and $A^{other}_{f,t}$, we use a similar procedure as equations (A.10) and (A.12). We create an estimate of the dollar amount of process innovation by the firm in year t as

$$\xi^{proc}_{f,t} = \sum_{j \in P_{f,t}} \theta_j \, \xi_j, \tag{A.14}$$

as well as the residual innovation $\xi^{other}_{f,t} = \xi_{f,t} - \xi^{proc}_{f,t}$. Similar to equation (A.12), we scale both measures by firm assets. In terms of magnitudes, the average fraction of the dollar value of firm innovation that can be characterized as process, $\xi^{proc}_{f,t}/\xi_{f,t}$, is approximately 27.5%.

C Methodology

Here, we relegate details of our estimation and simulation methodology.

C.1 Econometric Methodology

Quantile regression methods are semiparametric, allowing us to characterize features of conditional distributions without needing to fully specify distributional assumptions. Just as OLS regression methods estimate best linear projections of conditional expectation functions under misspecification, linear quantile regression methods estimate a (weighted) linear approximation of the true unknown quantile function. See Angrist, Chernozhukov, and Fernández-Val (2006) for further details. In contrast to alternative parametric methods for characterizing higher moments of non-Gaussian distributions (e.g., fitting mixture models), quantile regression methods are highly computationally tractable. We estimate the parameters of interest by solving a sequence of convex optimization problems which converge quickly even with a large number of observations (14.6 million) and conditioning variables (our baseline specification includes hundreds of regressors).

In our analysis, we use a method for estimating multiple conditional quantiles recently developed in Schmidt and Zhu (2016). This method, which is a natural extension to the location-scale paradigm, has the advantage of estimating conditional quantiles which are not susceptible to the well-known quantile crossing problem. Furthermore, as we will show in the next section, it allows for a natural interaction between aggregate and cross-sectional determinants of higher moments. In what follows, we briefly describe the procedure, and refer the reader to Schmidt and Zhu (2016) for more details.

Let $Y_{i,t}$ be the dependent variable of interest, and $X_{i,t}$ be a set of observable conditioning variables. In our case, $Y_{i,t}$ will be the growth rate of labor income, cumulated over various horizons. Let $q(\alpha; x)$ be the conditional quantile function of $Y_{i,t}$, for each $\alpha \in (0, 1)$, satisfying

$$q(\alpha; x) \equiv \inf\{y \in \mathbb{R}\colon P[Y_{i,t} \leq y \ \mid \ X_{i,t} = x] \geq \alpha\}. \tag{A.15}$$

If we further assume that the distribution of $Y_{i,t}$ is absolutely continuous, then $q(\alpha; x)$ is a continuous, strictly increasing function of α. Our interest will be in estimating a model for p conditional quantiles associated with the probability indices $\alpha_1, \dots, \alpha_p$, and we will denote the j^{th} conditional quantile of interest by $q_j(x) = q(\alpha_j; x)$. We assume throughout that $\alpha_{j^*} = \frac{1}{2}$ for $j^* \in \{1, \dots, p\}$, so $q_{j^*}(x)$ is the conditional median of $Y|X = x$.

Following Schmidt and Zhu (2016), we parameterize the conditional quantiles $q_j(x)$ by:

$$q_j(x) = \begin{cases} x'\beta_0 & \text{if } j = j^* \\ x'\beta_0 - \sum_{k=j}^{j^*-1} \exp(x'\beta_k) & \text{if } j < j^* \\ x'\beta_0 + \sum_{k=j^*+1}^{j} \exp(x'\beta_{k-1}) & \text{if } j > j^* \end{cases}. \tag{A.16}$$

The econometric model in (A.16) is a natural extension of the location-scale paradigm. All quantiles are anchored to the conditional median of $Y|X$ — which is denoted by $q_{j^*}(x)$. The quantiles above the median are estimated by adding nonnegative functions ("quantile spacings") which are exponentially affine in the independent variables $X_{i,t}$, which ensures that all quantiles will be properly ordered (e.g., the 75-th percentile will always be above the median).[23]

Our specification for multiple quantiles allows for considerable flexibility in higher moments above and beyond the location-scale benchmark in the previous section. For instance, spacings to the left of the median could be larger than spacings to the right of the median, which would indicate a left-skewed distribution of shocks. Or, alternatively, some variables could have a larger influence on more extreme spacings (such as the distance between the 10-th and 5-th percentile) relative to spacings closer to the median (such as the distance between the median and the 25-th percentile), generating variation in conditional kurtosis. Moreover, Schmidt and Zhu (2016) argue that a multiplicatively separable functional form like (A.16) can be motivated by the nonparametric extension of differences-in-differences estimation proposed by Athey and Imbens (2006).

The interpretation of an individual slope coefficient within one of the spacing functions is a

[23] Any sequence of conditional quantiles of an absolutely continuous random variable can be decomposed as a median plus or minus a sequence of non-negative distances of quantiles. For computational tractability, we require that the specification is *linear in parameters*. Schmidt and Zhu (2016) demonstrate how to estimate the model in (A.16) by iteratively applying a sequence of standard linear-in-parameters quantile regressions, beginning with the median and working toward the tails.

semi-elasticity. In particular, for any $j \neq j^*$, we have that

$$\beta_j = \frac{\partial}{\partial x}[\log(q_{j+1}(x) - q_j(x))], \tag{A.17}$$

which is the percentage change in the distance between two quantiles induced by a marginal change in x. A positive slope coefficient in a spacing below the median ($j < j^*$) indicates that, all else constant, increasing x increases downside risk, fattening the left tail. Positive coefficients in spacings above the median are associated with a fattening of the right tail.

We present our main results in terms of the average marginal effect of the independent variables x on a given quantile. These estimates incorporate the accumulated effect across quantiles. An advantage of our estimation methodology is that it results in highly tractable forms for these average marginal effects,

$$E\left[\frac{\partial q_j(X_{i,t})}{\partial X_{i,t}}\right] = \begin{cases} \beta_0 & \text{if } j = j^* \\ \beta_0 - \sum_{k=j}^{j^*-1} E[\exp(X'_{i,t}\beta_k)]\beta_k & \text{if } j < j^* \\ \beta_0 + \sum_{k=j^*+1}^{j} E[\exp(X'_{i,t}\beta_{k-1})]\beta_k & \text{if } j > j^* \end{cases}. \tag{A.18}$$

To estimate these average marginal effects, we use the sample means as plug-in estimators of the expectations. In some of our specifications, the particular coefficient of interest is an interaction term of a categorical variable with some other continuous variable (e.g., innovation). In these cases, we compute an average marginal effect for the subsample of workers within that category.

We compute standard errors using a block-resampling procedure that allows for persistence in the error terms at the firm level. Schmidt and Zhu (2016) establish the consistency, asymptotic normality, and consistency of a bootstrap inference procedure. For computational efficiency, we use a subsampling procedure rather than the bootstrap, noting that subsampling methods are generally valid under weaker conditions than the bootstrap. We estimate the variance-covariance matrix of the unknown vector of parameters by randomly selecting 10% firms without replacement, then scaling the variance-covariance matrix of the subsampled parameters appropriately using the asymptotic rate of convergence of the ($\sqrt{N}$-consistent) estimator. We also stratify these firm subsamples by 10 size bins. We use 100 replications.

To circumvent the incidental parameter bias, we exclude very small industries from the analysis. Specifically, we drop industries with less than 10,000 matched worker-year observations from the estimation. We impose the same restriction in the OLS estimates in Table 1 for comparability with later results.

C.2 Simulation Procedure

While our estimated model characterizes the distribution of income growth rates conditional on innovation, we can simulate from the model to see what our estimated coefficients imply about the evolution of inequality of income levels. To approximate the evolution of income inequality in levels, we use the following procedure.

We begin with an individual's log average residual earnings over the prior 3 years—the same measure which is subtracted off to calculate our growth rate measure—and add to it a randomly generated growth rate from the fitted quantile model. To do this, we interpolate between fitted quantiles to construct a smooth, continuously differentiable quantile function using a flexible parametric approach proposed in Schmidt and Zhu (2016). This approach allows us to efficiently simulate from the estimated conditional quantile model. Specifically, we construct a mapping from a set of 7 conditional quantiles to a smooth density function from $f(y;\mathbf{q}) \equiv f(y; q_1, \ldots, q_7) \colon \mathbb{R} \to \mathbb{R}_+$ by jointly imposing several restrictions:

1. To the left of q_2, $f(y, \mu_l)$ corresponds with a normal density with location and scale parameters chosen to match the conditional quantile restrictions: i.e., its cdf satisfies $\Phi(q_1, \mu_l, \sigma_l) = 0.05$ and $\Phi(q_2, \mu_l, \sigma_l) = 0.1$. Analogously, to the right of q_6, it follows a normal density $\phi(y, \mu_u, \sigma_u)$ which satisfies $\Phi(q_6, \mu_u, \sigma_u) = 0.90$ and $\Phi(q_7, \mu_u, \sigma_u) = 0.95$.

2. Between q_2 and q_6, the CDF is a cubic spline with knots at $\{q_2, ..., q_6\}$ which satisfies the conditional quantile restrictions, is continuous, and has continuous first and second derivatives. These restrictions can be cast as a linear system of equations which has an exact solution given two additional restrictions on the behavior of the spline at the boundaries. We impose that the CDF has a continuous first derivative (i.e., the implied density matches the normal used in the tails).

3. If the spline from part 2 is not strictly monotonic, we linearly interpolate the CDF instead.

Since our CDF is strictly increasing by construction, it is also straightforward to compute the quantile function $Q(u; \mathbf{q})$ by inverting it.

Since the spline is defined using a system of (tridiagonal) linear equations, we can quickly and efficiently solve jointly for the spline parameters for a large number of observations at once. Our simulation exercise is performed as follows:

1. For each individual, using the observed values of income growth y_{it} and covariates x_{it}, compute the CDF of person i's income growth realization: $\hat{u}_{it} \equiv F(y_{it}; \mathbf{q}(\mathbf{x_{it}}, \hat{\beta}))$. $\hat{u}_{it}$ is the percentile of the shock that person i received at time t according to our fitted quantile model.

2. Then, we compute the counterfactual income growth realization as $\tilde{y}_{it} \equiv Q(\hat{u}_{it}; \mathbf{q}(\tilde{\mathbf{x}}_{\mathbf{it}}, \hat{\beta}))$, where $\tilde{x}_{it}$ is a set of counterfactual variables. Note that $\tilde{y}_{it} = y_{it}$ if $\tilde{x}_{it} = x_{it}$.[24]

3. The counterfactual income level is computed by adding the lagged level to the simulated income growth realization $\tilde{y}_{it}$.

The simulated draws associated with the covariates from year t provide an estimate of the cross-sectional distribution of average income from $t + 1$ through $t + 5$ implied by the baseline model when we use the actual values of x_{it} observed in the data.[25] Other than some minor differences in levels introduced by truncation of extreme growth rates in individual earnings[26], our method reproduces the empirical distribution of income levels at each period. The realized change line in Figure 8 is computed by taking the log difference between the set of simulated income statistics in year t relative to the the same statistic for year $t - 5$ times 100, expressed in annualized units (by dividing by 5).

We then compare this realized change with an analogous set of simulations using the fitted quantile functions that obtain when we change the firm and competitor innovation measures, holding all other individual and firm-specific variables fixed. By comparing the simulated level of inequality obtained from these alternative scenarios with the baseline specification, we obtain a model-implied decomposition of the potential contribution of innovation in year t to inequality, relative to this

[24] To minimize the influence of outliers and avoid numerical instabilities related to evaluating inverse functions, we truncate $\hat{u}_{it}$ to the [0.0005,0.9995] interval. Therefore, the simulated draws exhibit slightly less dispersion relative to the original data. We use the same adjustment for both "actual" and counterfactual series, which still allows for an apples-to-apples comparison.

[25] In an earlier draft, we simulated draws from our estimated model for income growth rates by drawing a sample of i.i.d uniform random variables, then evaluate the interpolated quantile function at these points. While results were similar, our current approach has the advantage of maintaining the correlation structure of income realizations across workers at each point in time.

[26] We verify that growth rates associated with the truncated series and raw sample moments are essentially identical.

alternative scenario. Such a calculation is similar in spirit to the decomposition exercises of Machado and Mata (2005) and Firpo, Fortin, and Lemieux (2011), which seek to quantify the predicted effect of changes in the distribution of explanatory variables on quantiles of the unconditional distribution of an outcome variable. While these decompositions do not necessarily have a causal interpretation, they help to shed light on the magnitudes associated with our estimated coefficients.

We compare the simulated levels of earnings inequality implied by the observed distribution of innovation across firms with a simple alternative scenario which replaces $A_{f,t}$ and $A_{I\setminus f,t,t}$ with their equal weighted means across firms within the industry in a given year: $\frac{1}{N_{I(f),t}}\sum_{f\in I(f)} A_{f,t}$ and $\frac{1}{N_{I(f),t}}\sum_{f\in I(f)} A_{I\setminus f,t,t}$, respectively. Whereas the observed distribution of innovation is unequally distributed across firms, this calculation assumes instead that it is symmetric within a given industry-year, but allows for heterogeneity across industries and over time.

We also ran a version of the simulation exercise which replaces $A_{f,t}$ and $A_{I\setminus f,t,t}$ with averages calculated across all firm-years within the same industry for the 1980-1984 period. In this case, in addition to imposing symmetry, we shut down time series variation in the level of innovation within an industry, noting that innovation later in our sample period was generally higher than the observed levels in 1980-1984. Comparing the first and second scenarios speaks to the effects of time-series variation in average industry-level innovation which occurred during our sample period. We find that results are fairly similar to the simulation exercise in the main paper, suggesting the dominant force is actually within-industry heterogeneity in innovation at the same point in time, rather than variation in the level of innovation over time, that drives our main results. These results have been suppressed for brevity.

We compute two simple univariate statistics to summarize the changes in inequality induced by these changes in the innovation measures (results are similar for other percentiles) in the right tail and left tail of the distribution of income, respectively. To capture changes in the right tail, we compute the log difference (times 100) between distance between the 95^th and 50^th percentiles of earnings levels from the baseline and alternative models. Analogously for the left tail, we compare the distances 50^th and 5^th percentiles of earnings levels between baseline and alternative simulations. While we focus on these statistics for brevity, results are similar for other percentiles.

We also decompose the implied changes in inequality into in between and within-firm components. For this analysis, we require that a firm is associated with at least 20 observations in a given year. Our approach follows the construction of Song et al. (2019). For each individual in our sample, we compute the average level of simulated log earnings associated with all of the his coworkers as of time t. We then separately plot the changes in the distribution of average firm log earnings and the distribution of within-firm earnings, which is defined by subtracting the firm-level average from an individual's log earnings. There are two key differences between our construction and the one in Song et al. (2019). First, our earnings measure is cumulated over a longer period of time. Second, firm average earnings are defined relative to the set of coworkers as of time t, which eliminates the need to define a new set of co-workers for purposes of the decomposition.

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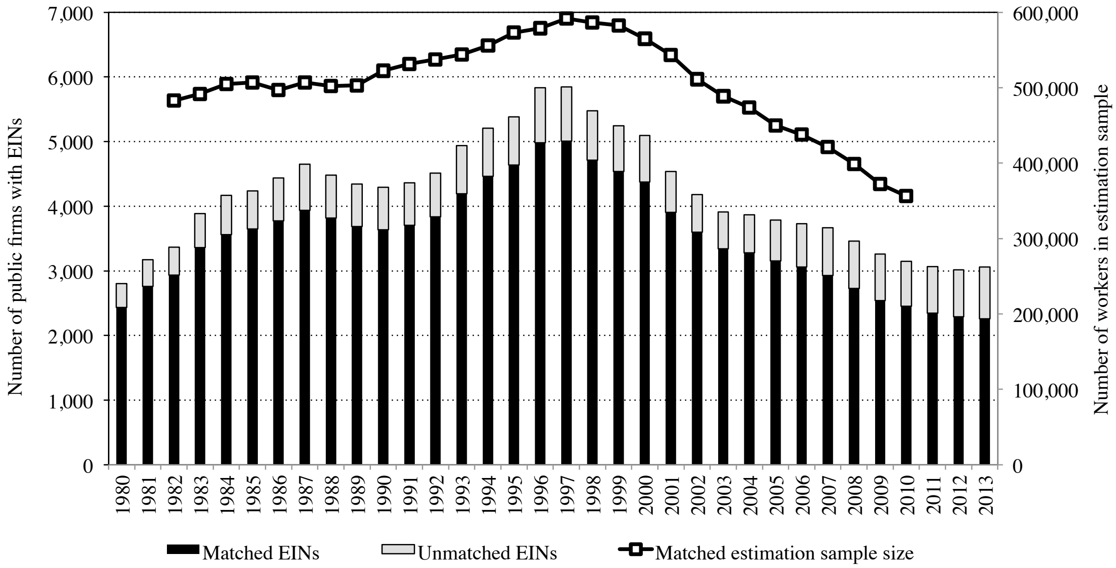
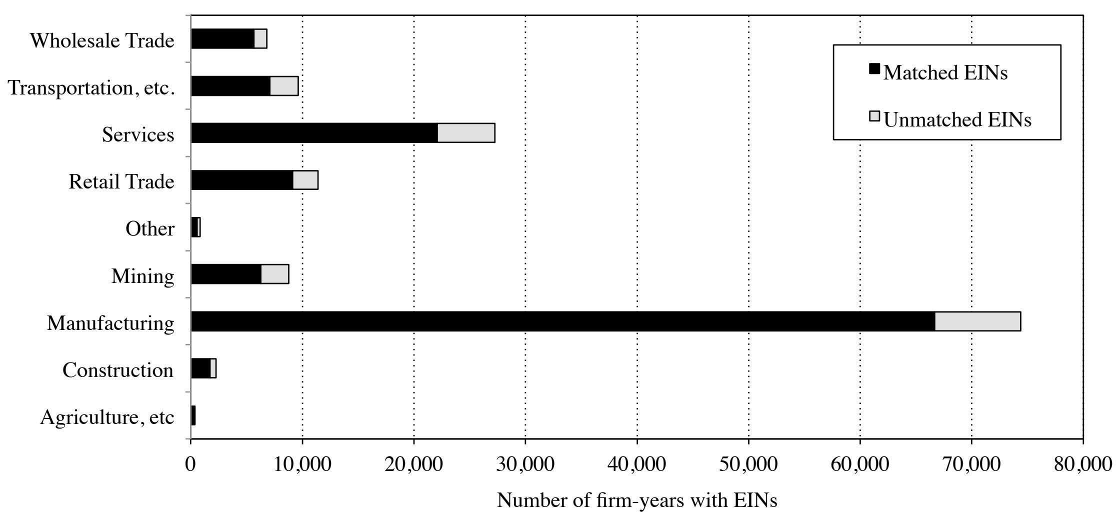
Appendix Tables and Figures

Figure A.1: Characteristics of the matched sample

Panel A: Number of observations by year

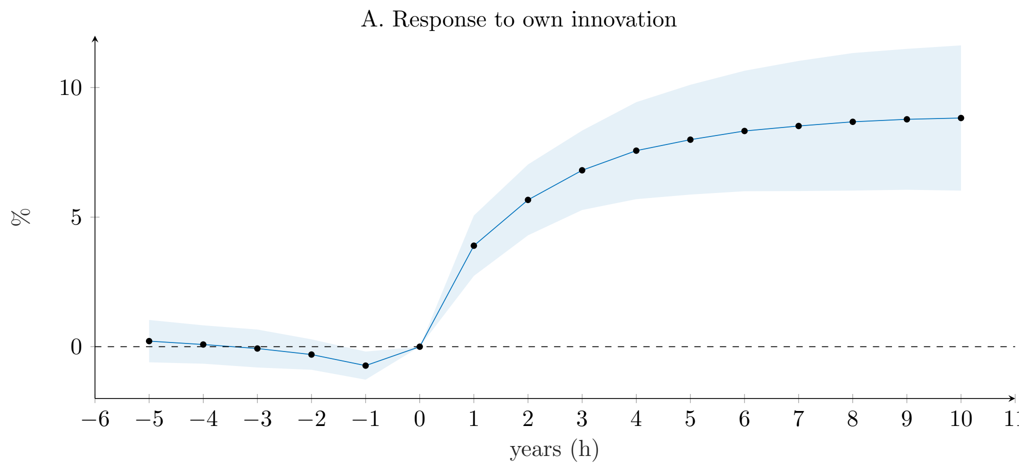


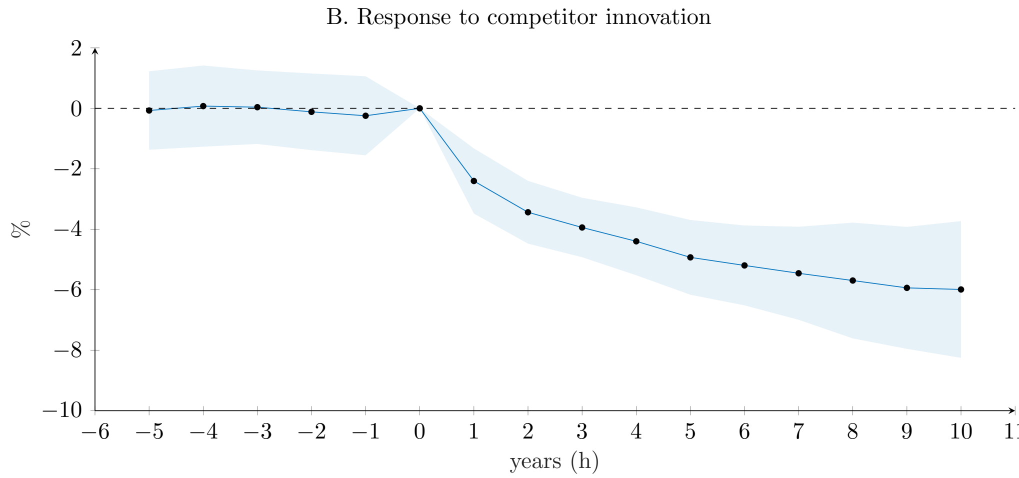
Panel B: Number of observations by major SIC sector



Note: The top plot provides counts of the number of public-firm years for which we can find matched W-2 earnings records in the SSA master earnings file, as well as the number of firm-years for which no earnings records could be found. We exclude firm-years for which no EIN is available. The bottom panel repeats the analysis by major SIC sector, where the SIC codes are taken from firms' financial statements.

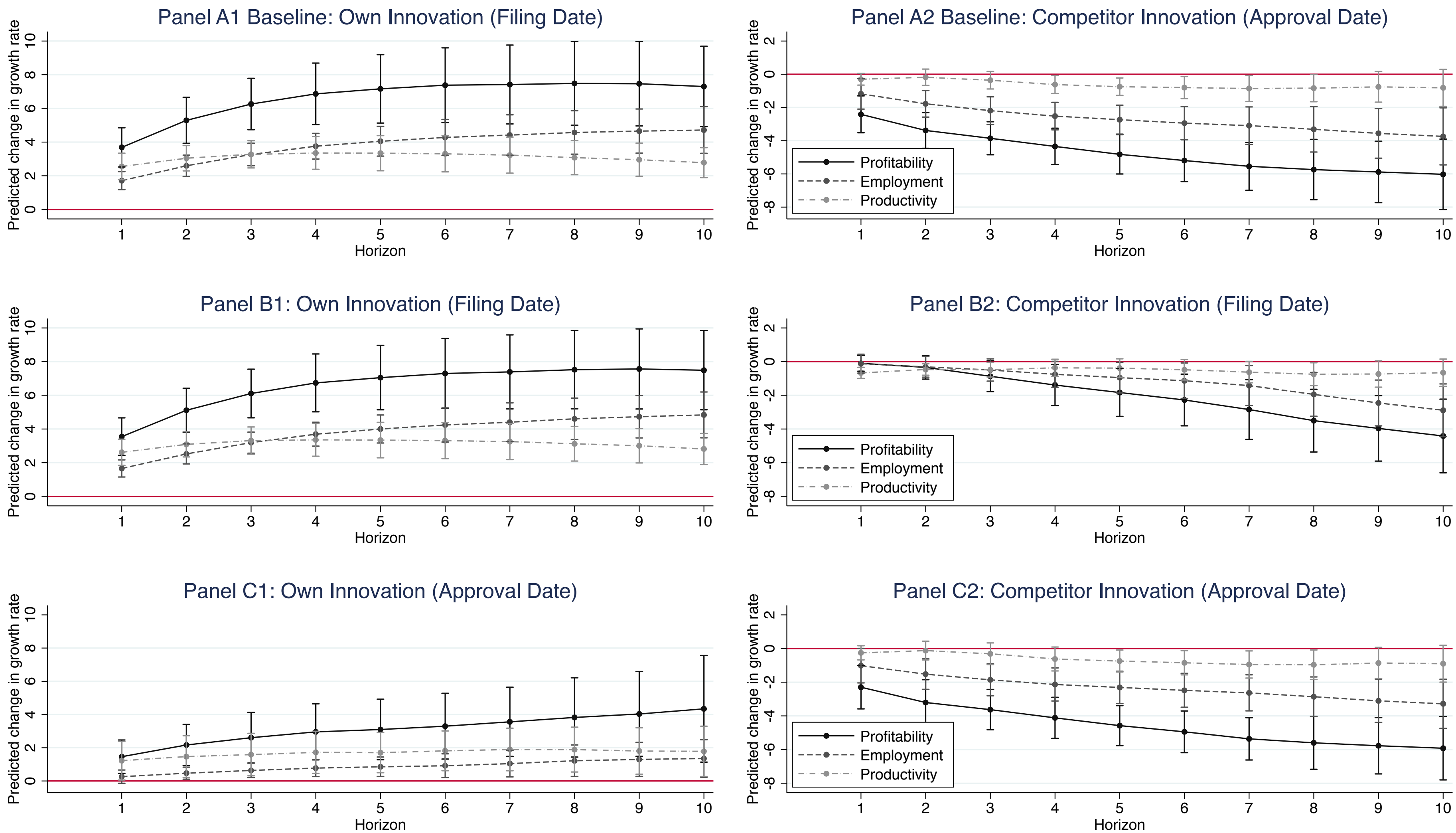
Figure A.2: Firm profitability and innovation across horizons





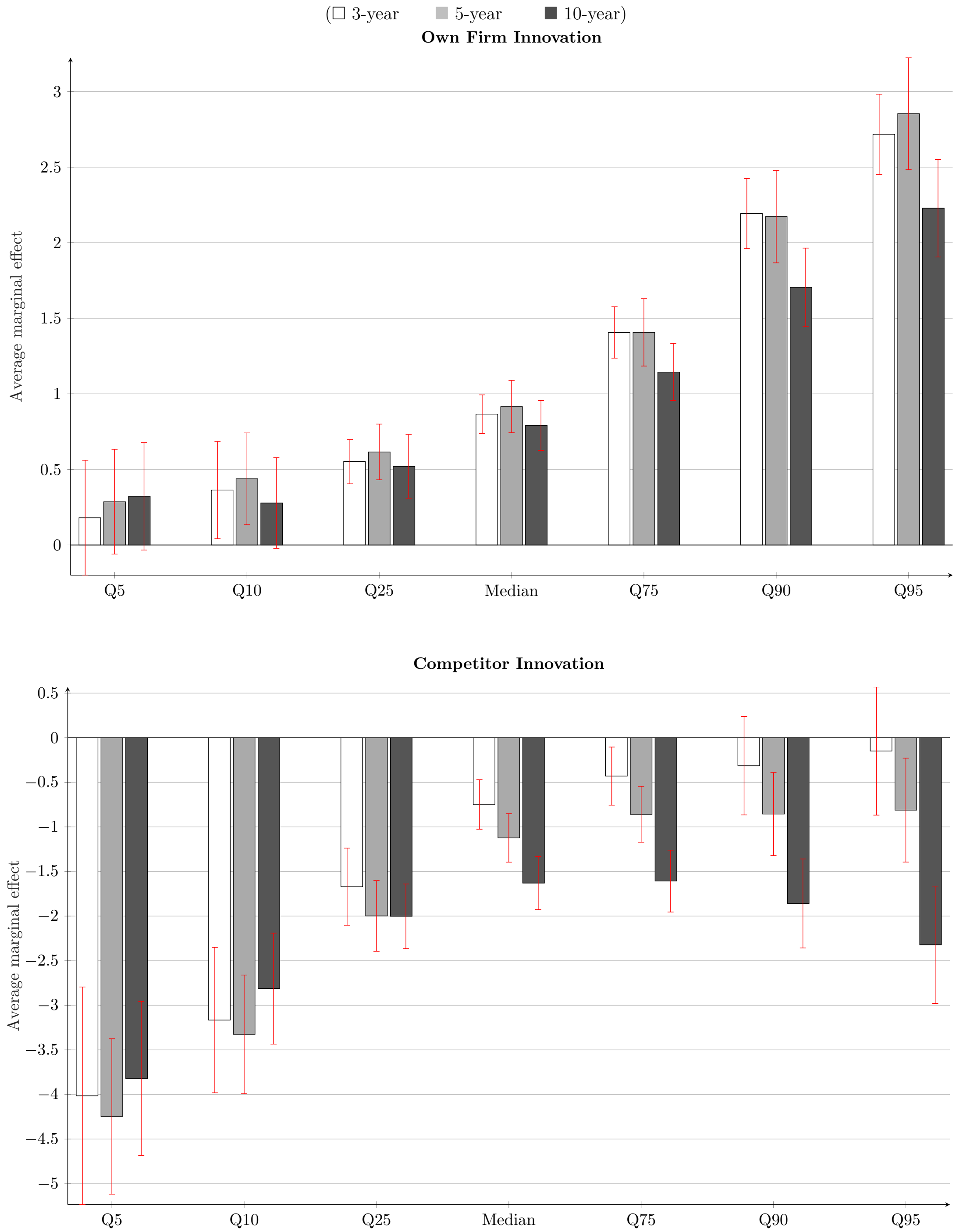
Note: Figure plots the estimated coefficients a_h (Panel A) and b_h (Panel B) from equation (11) in the main text, as we vary the horizon over which compute profits from $h = -5$ to $h = 10$. The estimated coefficient a_h (b_h) corresponds to the relation between the firm's average profits between years $t + 1$ to $t + h$ and and a 1 standard deviation change in own firm (competitor) innovation at time t; negative values for h correspond to average profits prior to time t, e.g. from $t - h$ to $t - 1$. Bars correspond to 95% confidence intervals computed with standard errors that are clustered by firm and time.

Figure A.3: Innovation and growth - Firm-level outcomes across horizons, varying timing conventions



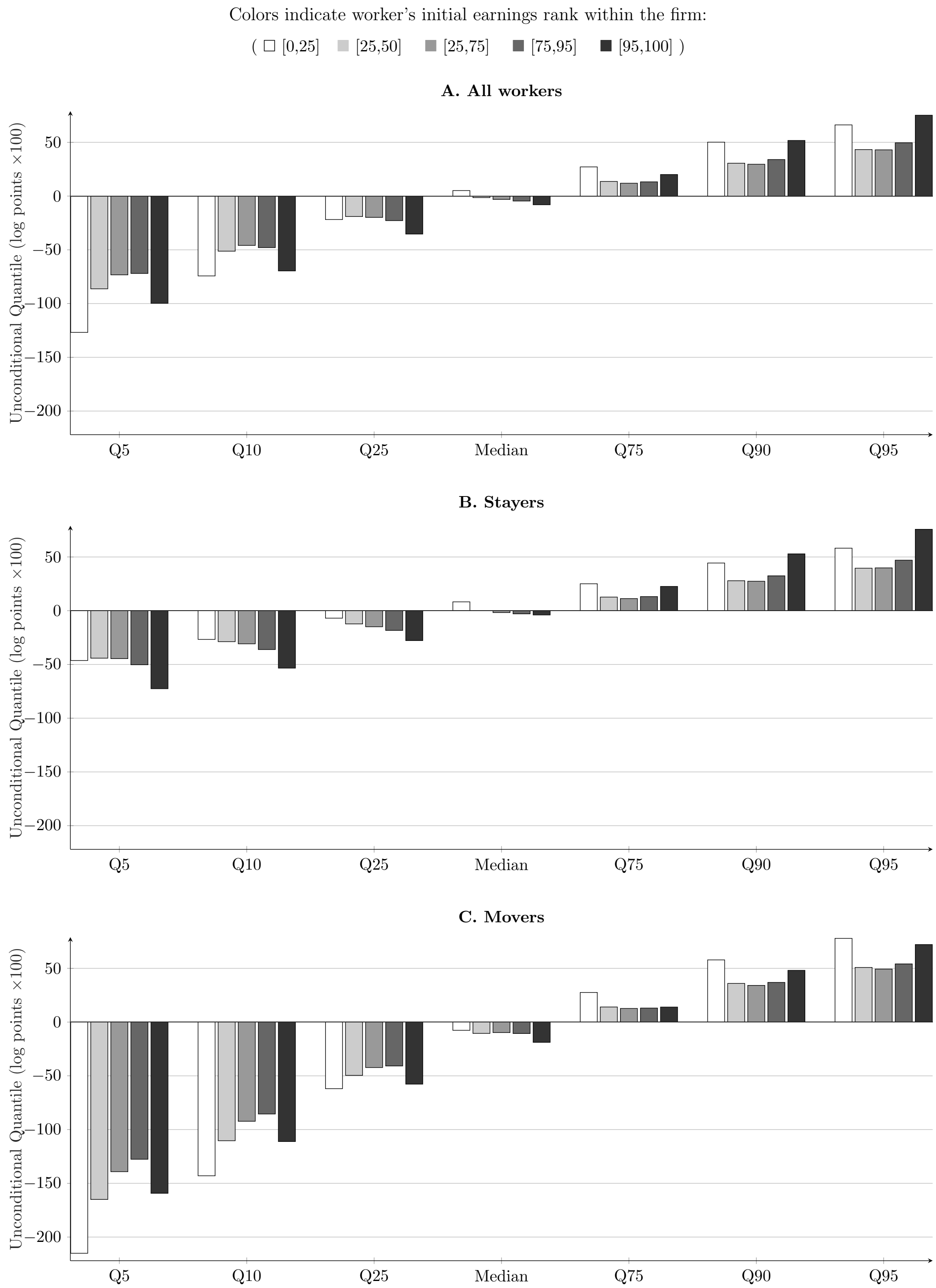
Note: Figure reports coefficient estimates of equation (11) for firm profits, employment and TFPR. The horizontal axis varies the horizon of the regression. Each dependent variable corresponds with a different line on the graph. Each specification relates firm growth to innovation by the firm (A_f, defined in equation (9) and the innovation by the firm's competitors ($A_{I\setminus f}$, the average innovation of other firms in the same SIC3 industry, see equation (10)). Panels B and C run the same regressions, changing the timing convention of own and competitor innovation measures to use the filing and approval dates, respectively. Controls include one lag of the dependent variable, log values of firm capital, employment, and the firm's idiosyncratic volatility, and industry (I) and time (T) fixed effects. All firm-level variables are winsorized at the 1% level using annual breakpoints. Standard errors are clustered by firm and year. All right-hand side variables are scaled to unit standard deviation.

Figure A.4: Earnings growth and innovation across horizons



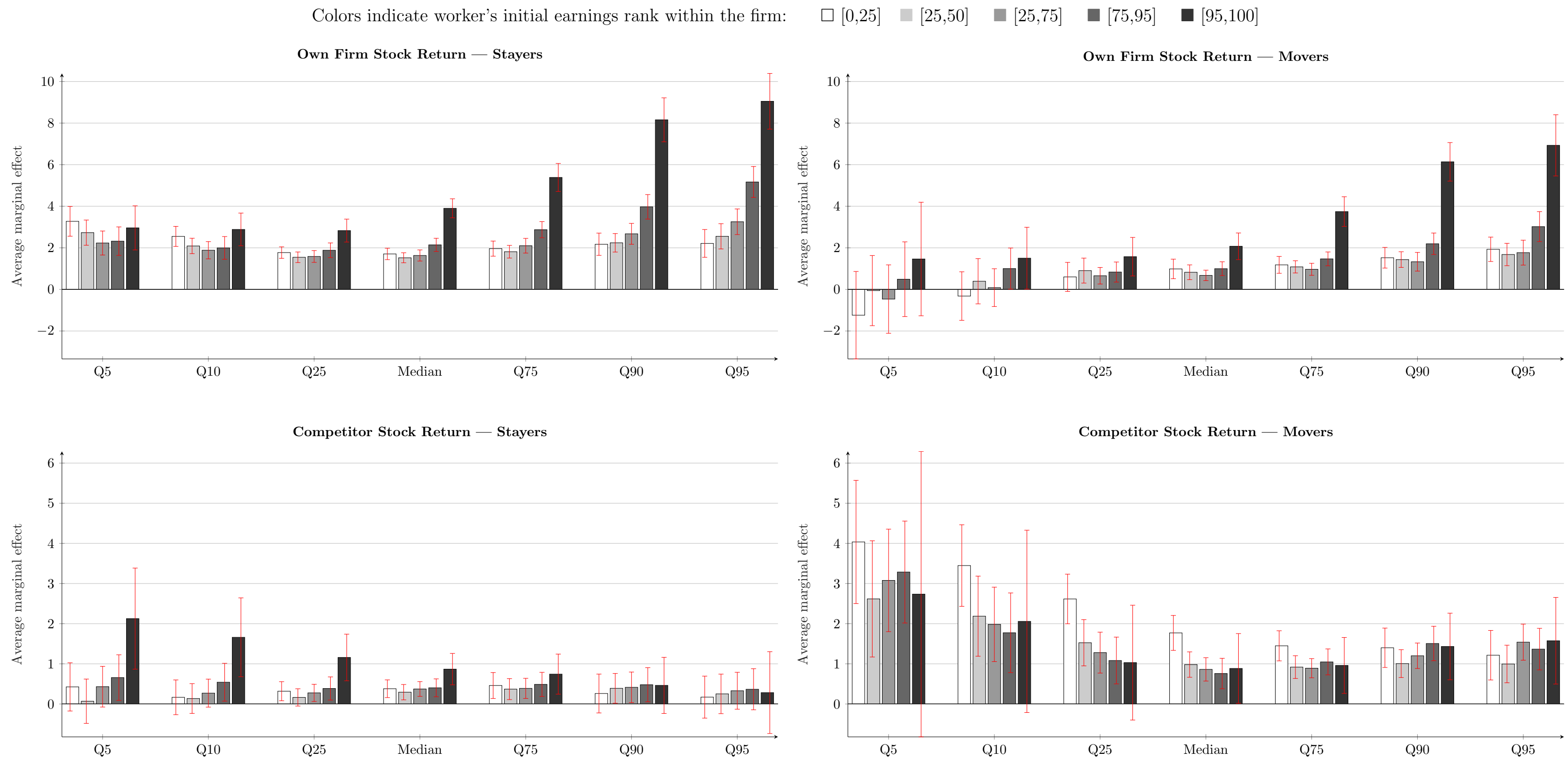
Note: Figure plots the average marginal effects of firm—and competitor—innovation that are implied by the quantile regression estimates (equation (12) in the main text) across different horizons (number of years of cumulative future earnings included in earnings growth), where estimates are scaled to correspond with a 1 standard deviation change in each variable of interest. The units on the vertical axis correspond to log points (times 100).

Figure A.5: Percentiles of income growth: movers versus continuing workers



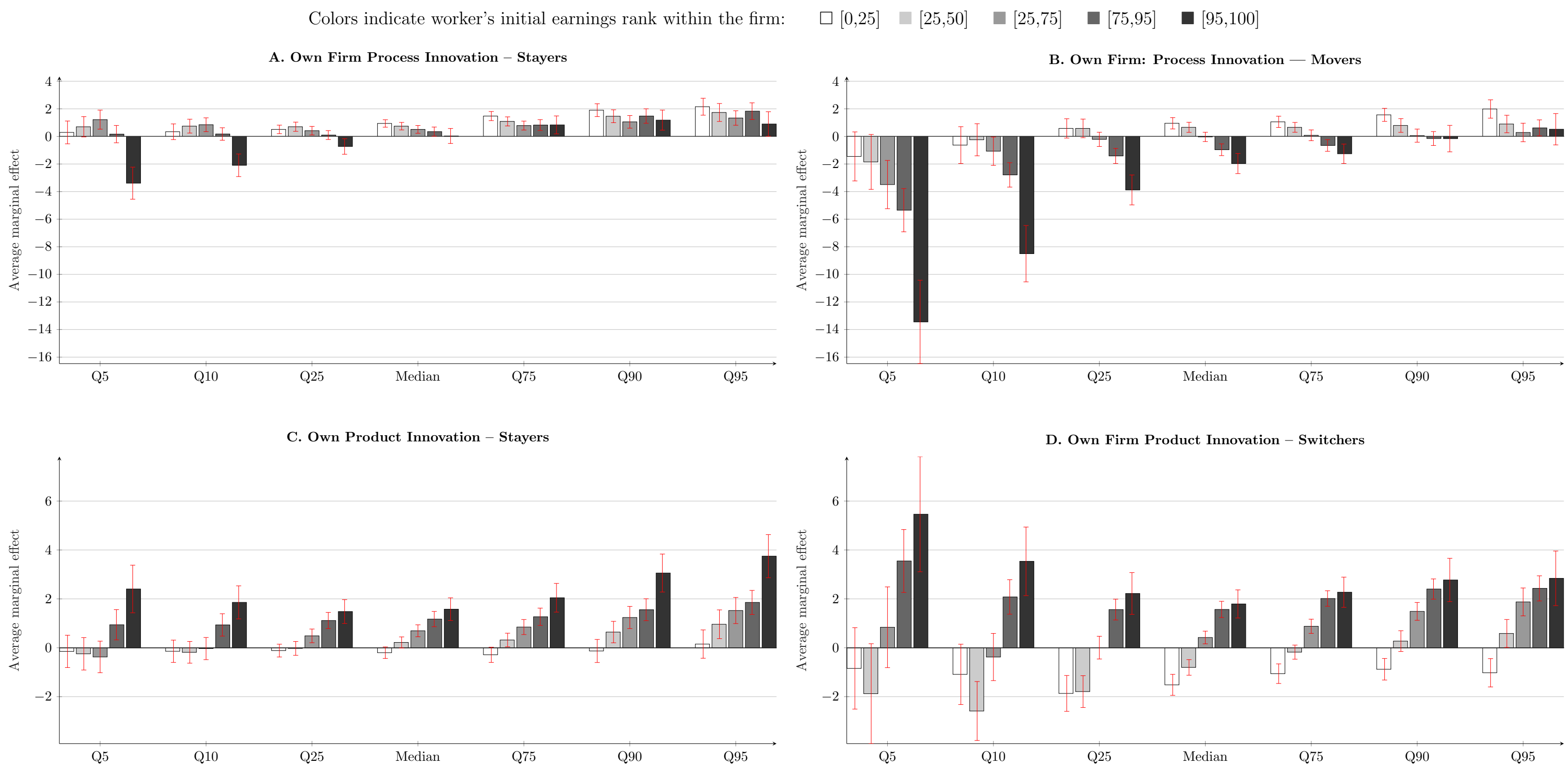
Note: Figure plots the distribution of 5-year earnings growth for workers of different earnings levels (earnings ranks) separately for workers that remain with the same firm after 5 years (stayers) and for those that do not (movers). The top panel plots the average fitted quantiles from the same specification as Figure 4. The middle panel presents coefficients from the same specification, estimated for the subsample of movers–workers who are employed at the firm in year t+3; while the bottom panel estimates the same model on workers who are not employed at the same firm in year t+3. These figures are based on average conditional quantiles from the estimated model. In general, he average conditional quantiles need not correspond to the unconditional quantiles for each group (Firpo et al., 2011). However, in our case they do. Appendix Figure A.14 shows these average predicted quantiles are quite similar to the unconditional quantiles in the data.

Figure A.6: Firm stock returns and innovation: movers versus continuing workers



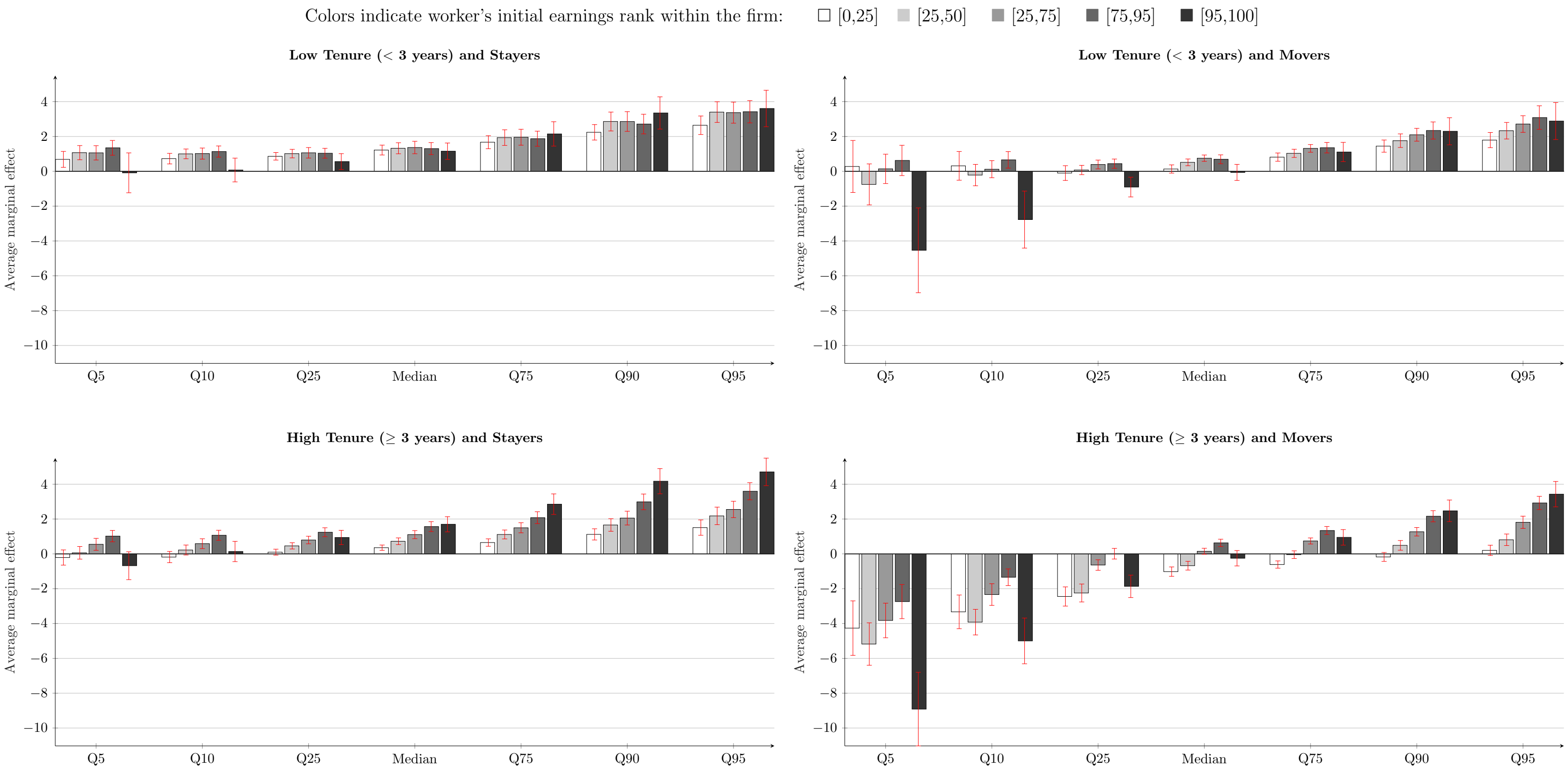
Note: Figure plots the average marginal effects of firm—and competitor—stock returns that are implied by the quantile regression estimates (analogous to equation (12) in the main text, except that we use own firm and competitor year t returns in place of the innovation measures) for workers with different earnings levels. Estimates are standardized to correspond with 1 standard deviation effects for each variable of interest. The equation is estimated separately for workers that remain with the firm (stayers) versus workers that leave the firm (switchers). The worker earnings rank is defined net of deterministic life-cycle effects. We focus on 5-year growth rates. The units on the vertical axis correspond to log points (times 100).

Figure A.7: Earnings growth and own firm process/product innovation conditional on worker earnings levels: movers versus continuing workers



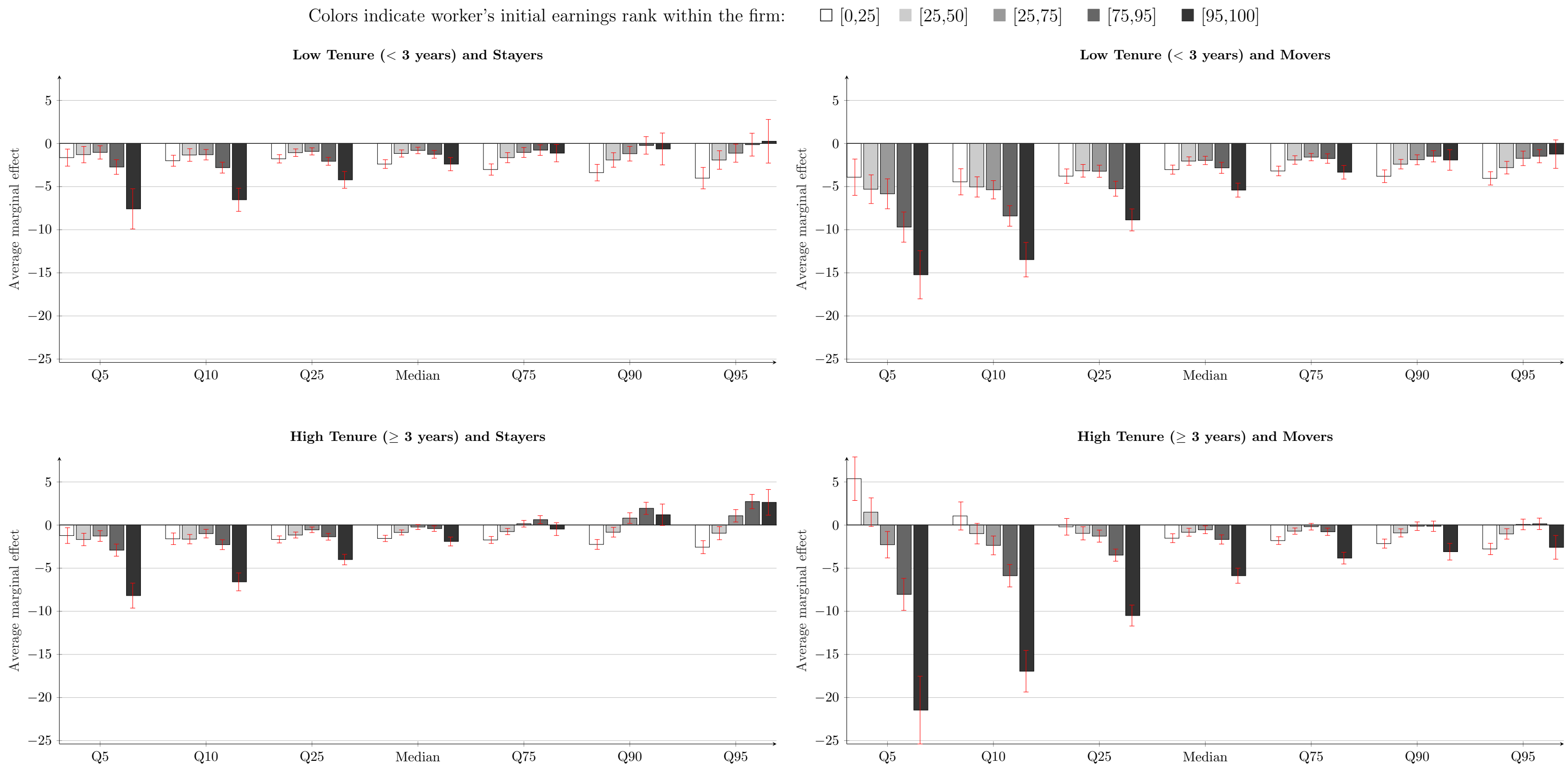
Note: Figure plots the average marginal effects of firm process/product innovation that are implied by the quantile regression estimates (equation (12) in the main text) for workers with different earnings levels. Estimates are standardized to correspond with 1 standard deviation effects for each variable of interest. The equation is estimated separately for workers that remain with the firm (stayers) versus workers that leave the firm (switchers). The worker earnings rank is defined net of deterministic life-cycle effects. We focus on 5-yr growth rates. The units on the vertical axis correspond to log points (times 100).

Figure A.8: Earnings growth and own firm innovation conditional on worker earnings levels and tenure: movers versus continuing workers



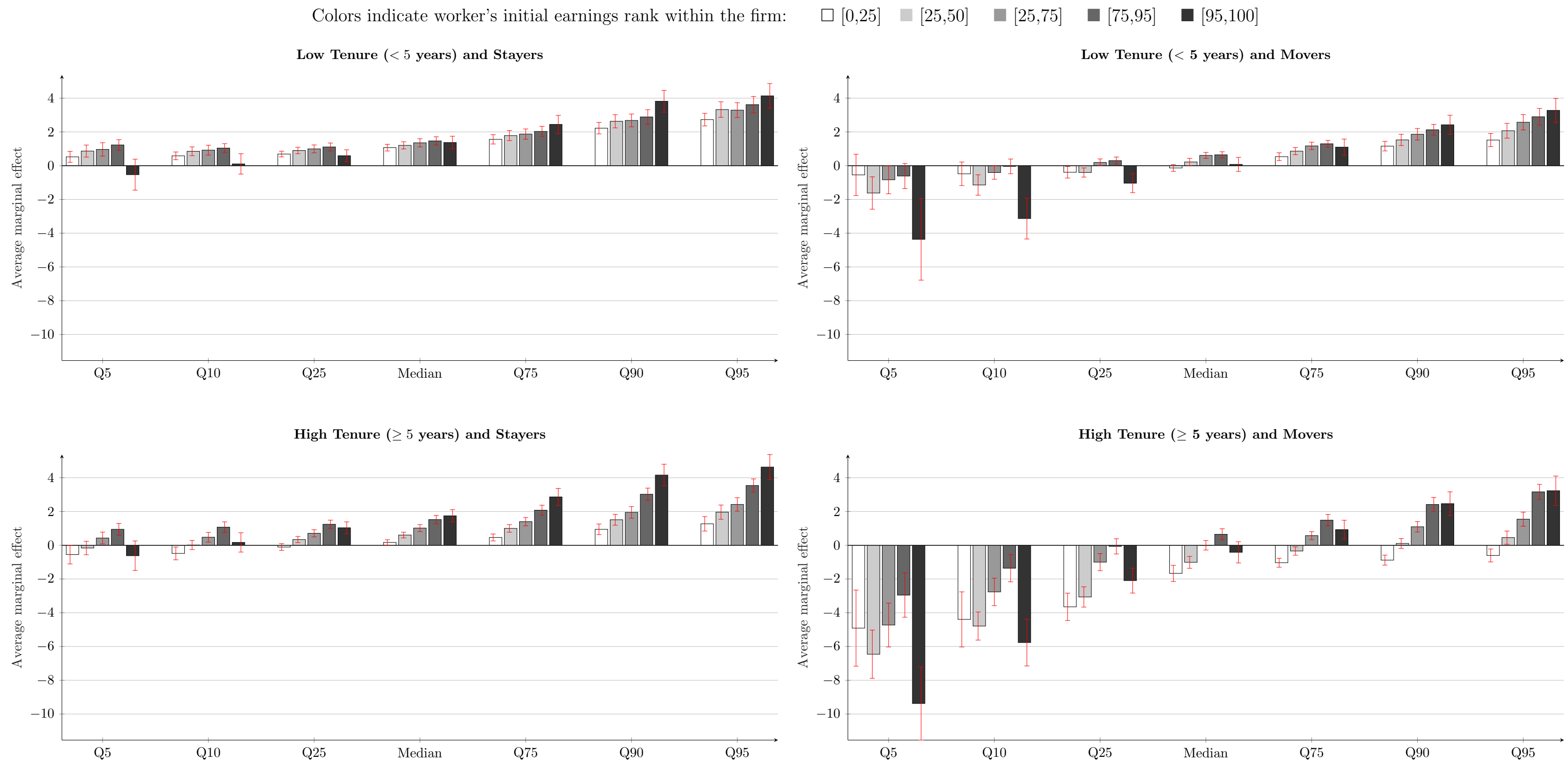
Note: Figure plots the average marginal effects of firm innovation that are implied by the quantile regression estimates (equation (12) in the main text) for workers with different earnings levels and years of tenure with the firm. Workers are sorted into two groups based upon whether they have less than 3 years or greater than or equal to 3 years of tenure, and we allow for separate coefficients for each tenure × lagged earnings bin. Estimates are standardized to correspond with 1 standard deviation effects for each variable of interest. The equation is estimated separately for workers that remain with the firm (stayers) versus workers that leave the firm (switchers). The worker earnings rank is defined net of deterministic life-cycle effects. We focus on 5-year growth rates. The units on the vertical axis correspond to log points (times 100).

Figure A.9: Earnings growth and competitor innovation conditional on worker earnings levels and tenure: movers versus continuing workers



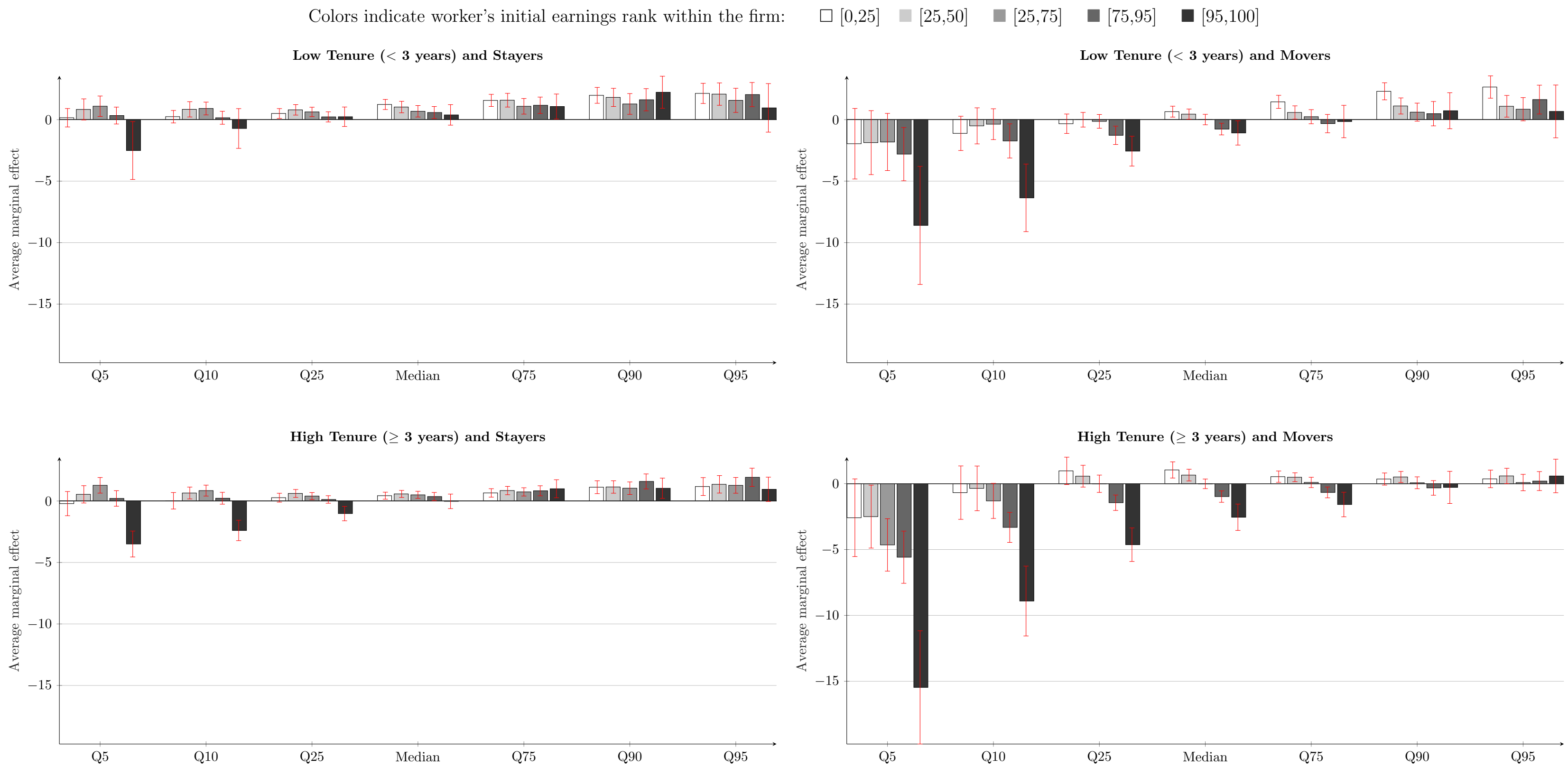
Note: Figure plots the average marginal effects of firm innovation that are implied by the quantile regression estimates (equation (12) in the main text) for workers with different earnings levels and years of tenure with the firm. Workers are sorted into two groups based upon whether they have less than 3 years or greater than or equal to 3 years of tenure, and we allow for separate coefficients for each tenure × lagged earnings bin. Estimates are standardized to correspond with 1 standard deviation effects for each variable of interest. The equation is estimated separately for workers that remain with the firm (stayers) versus workers that leave the firm (switchers). The worker earnings rank is defined net of deterministic life-cycle effects. We focus on 5-year growth rates. The units on the vertical axis correspond to log points (times 100).

Figure A.10: Earnings growth and own firm innovation conditional on worker earnings levels and tenure: movers versus continuing workers (5 year cutoff)



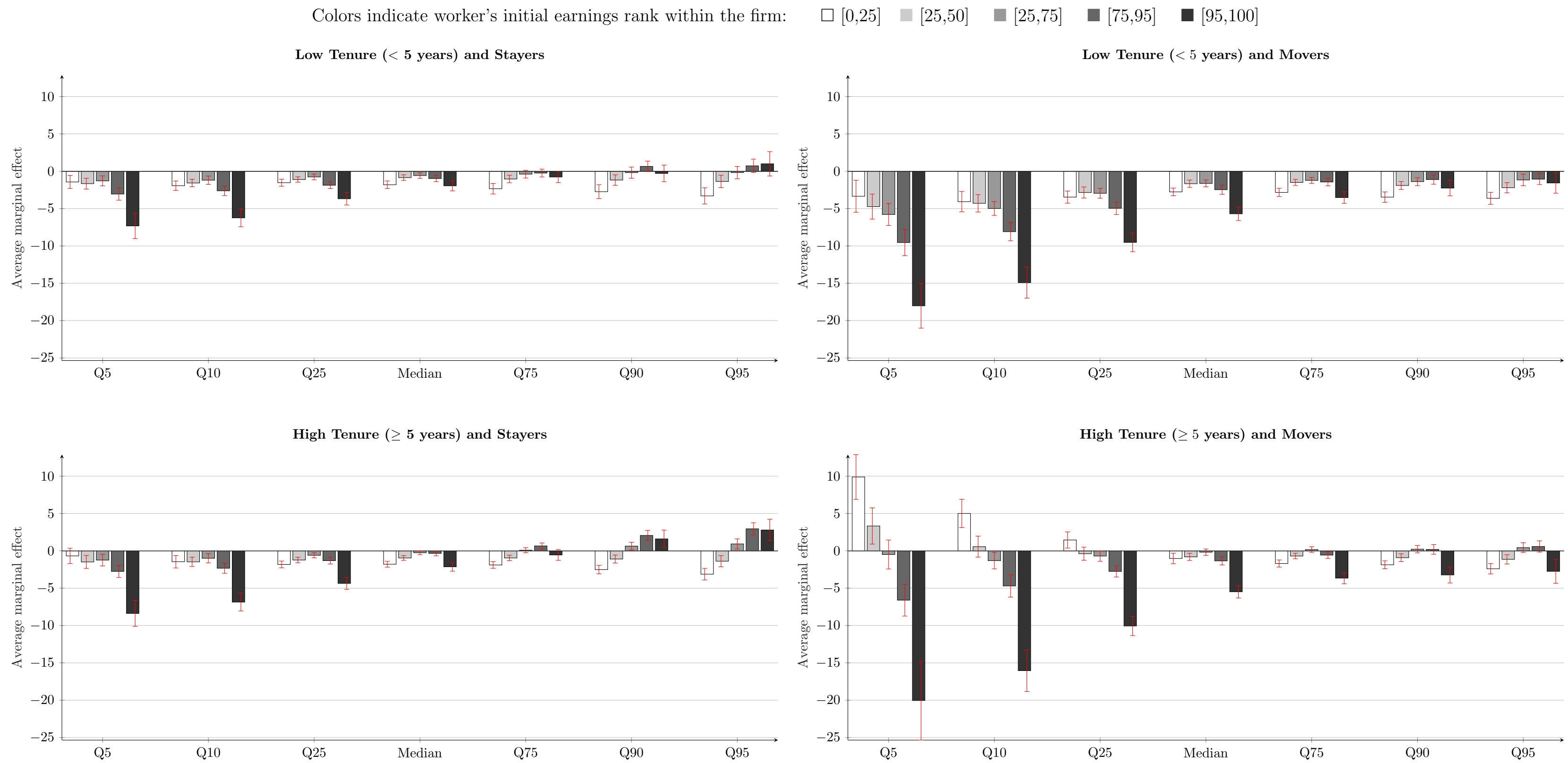
Note: Figure plots the average marginal effects of firm innovation that are implied by the quantile regression estimates (equation (12) in the main text) for workers with different earnings levels and years of tenure with the firm. Workers are sorted into two groups based upon whether they have less than 5 years or greater than or equal to 5 years of tenure, and we allow for separate coefficients for each tenure × lagged earnings bin. Estimates are standardized to correspond with 1 standard deviation effects for each variable of interest. The equation is estimated separately for workers that remain with the firm (stayers) versus workers that leave the firm (switchers). The worker earnings rank is defined net of deterministic life-cycle effects. We focus on 5-yr growth rates. The units on the vertical axis correspond to log points (times 100).

Figure A.11: Earnings growth and own firm process innovation conditional on worker earnings levels and tenure: movers versus continuing workers



Note: Figure plots the average marginal effects of firm process innovation that are implied by the quantile regression estimates (equation (12) in the main text) for workers with different earnings levels and for workers with different earnings levels and years of tenure with the firm. Workers are sorted into two groups based upon whether they have less than 3 years or greater than or equal to 3 years of tenure, and we allow for separate coefficients for each tenure × lagged earnings bin. Estimates are standardized to correspond with 1 standard deviation effects for each variable of interest. The equation is estimated separately for workers that remain with the firm (stayers) versus workers that leave the firm (switchers). The worker earnings rank is defined net of deterministic life-cycle effects. We focus on 5-yr growth rates. The units on the vertical axis correspond to log points (times 100).

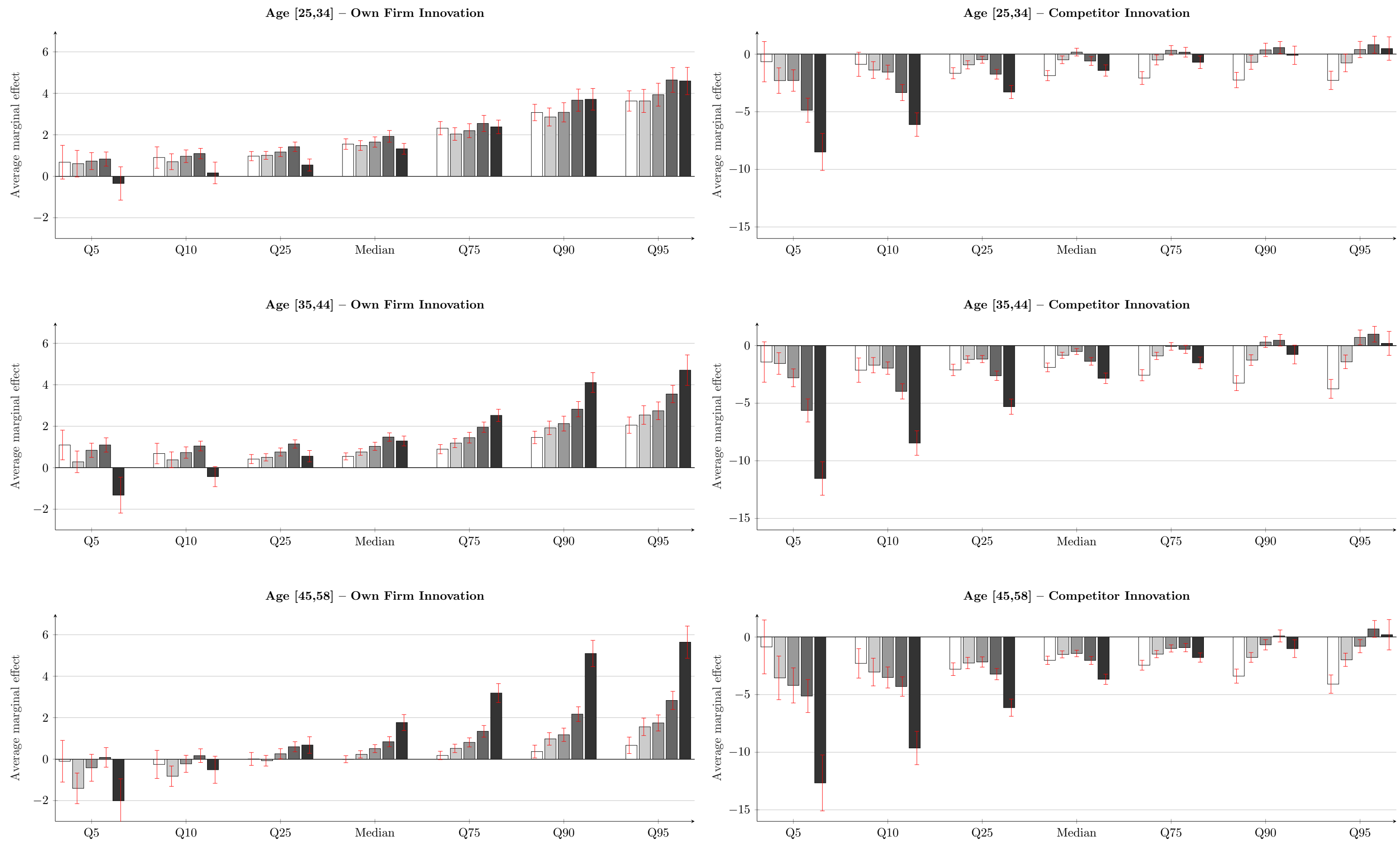
Figure A.12: Earnings growth and competitor innovation conditional on worker earnings levels and tenure: movers versus continuing workers (5 year cutoff)



Note: Figure plots the average marginal effects of firm innovation that are implied by the quantile regression estimates (equation (12) in the main text) for workers with different earnings levels and years of tenure with the firm. Workers are sorted into two groups based upon whether they have less than 5 years or greater than or equal to 5 years of tenure, and we allow for separate coefficients for each tenure × lagged earnings bin. Estimates are standardized to correspond with 1 standard deviation effects for each variable of interest. The equation is estimated separately for workers that remain with the firm (stayers) versus workers that leave the firm (switchers). The worker earnings rank is defined net of deterministic life-cycle effects. We focus on 5-year growth rates. The units on the vertical axis correspond to log points (times 100).

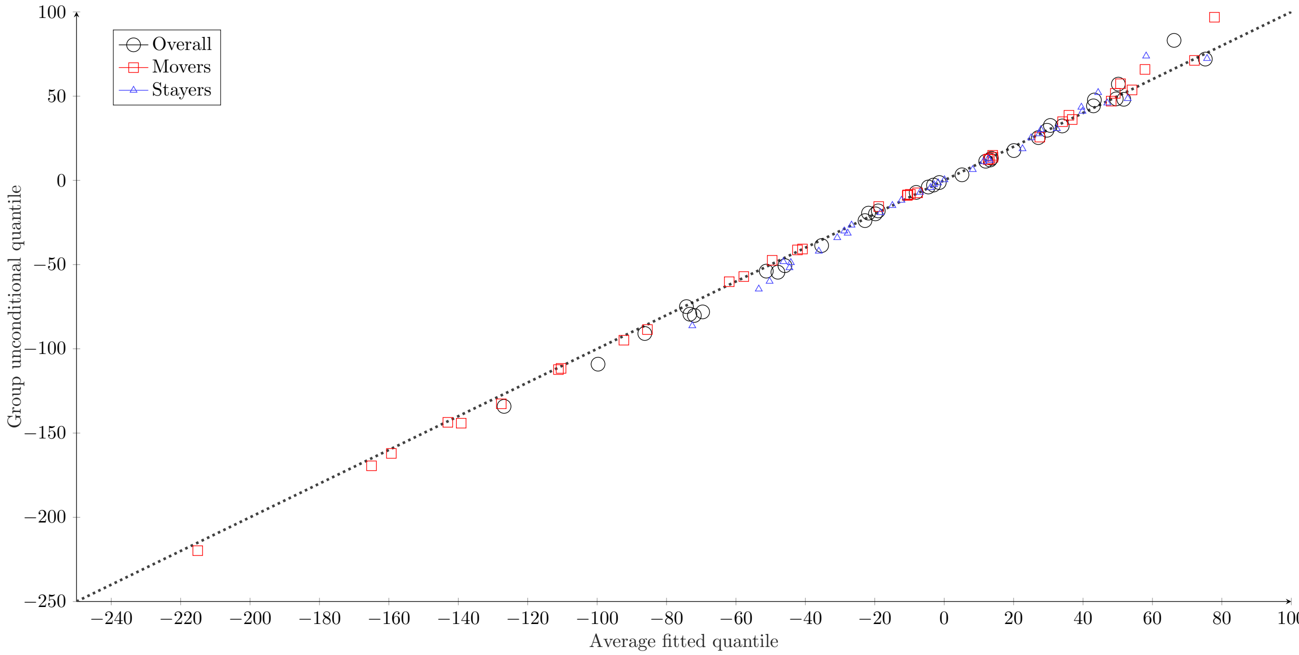
Figure A.13: Earnings growth and innovation conditional on age and earnings levels

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



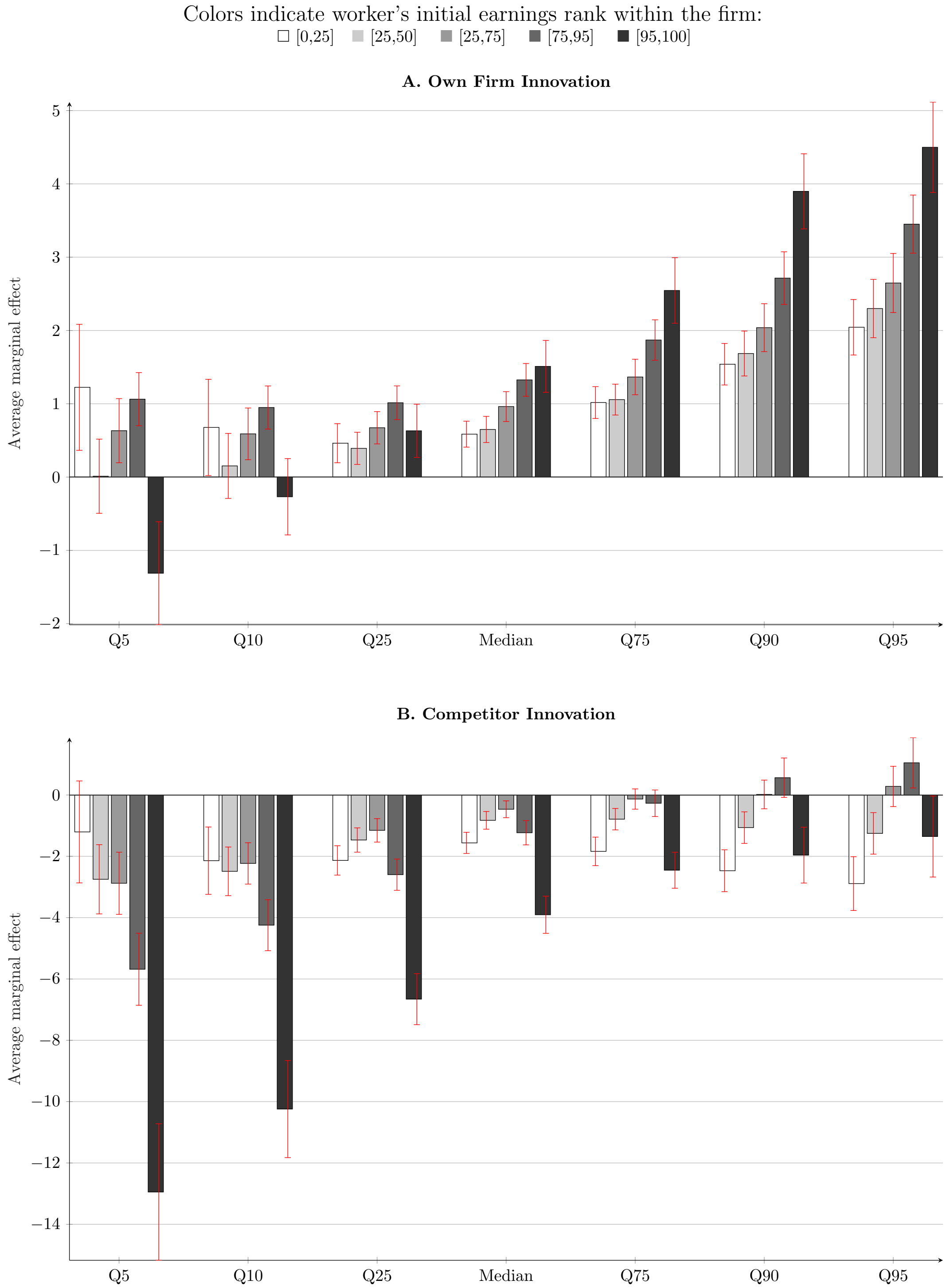
Note: Figure plots the average marginal effects of firm innovation that are implied by the quantile regression estimates (equation (12) in the main text) for workers with different ages and earnings levels. Estimates are standardized to correspond with 1 standard deviation effects for each variable of interest. The worker earnings rank is defined net of deterministic life-cycle effects. We focus on 5-year growth rates. The units on the vertical axis correspond to log points (times 100).

Figure A.14: Unconditional quantiles versus average fitted quantiles by firm rank bin



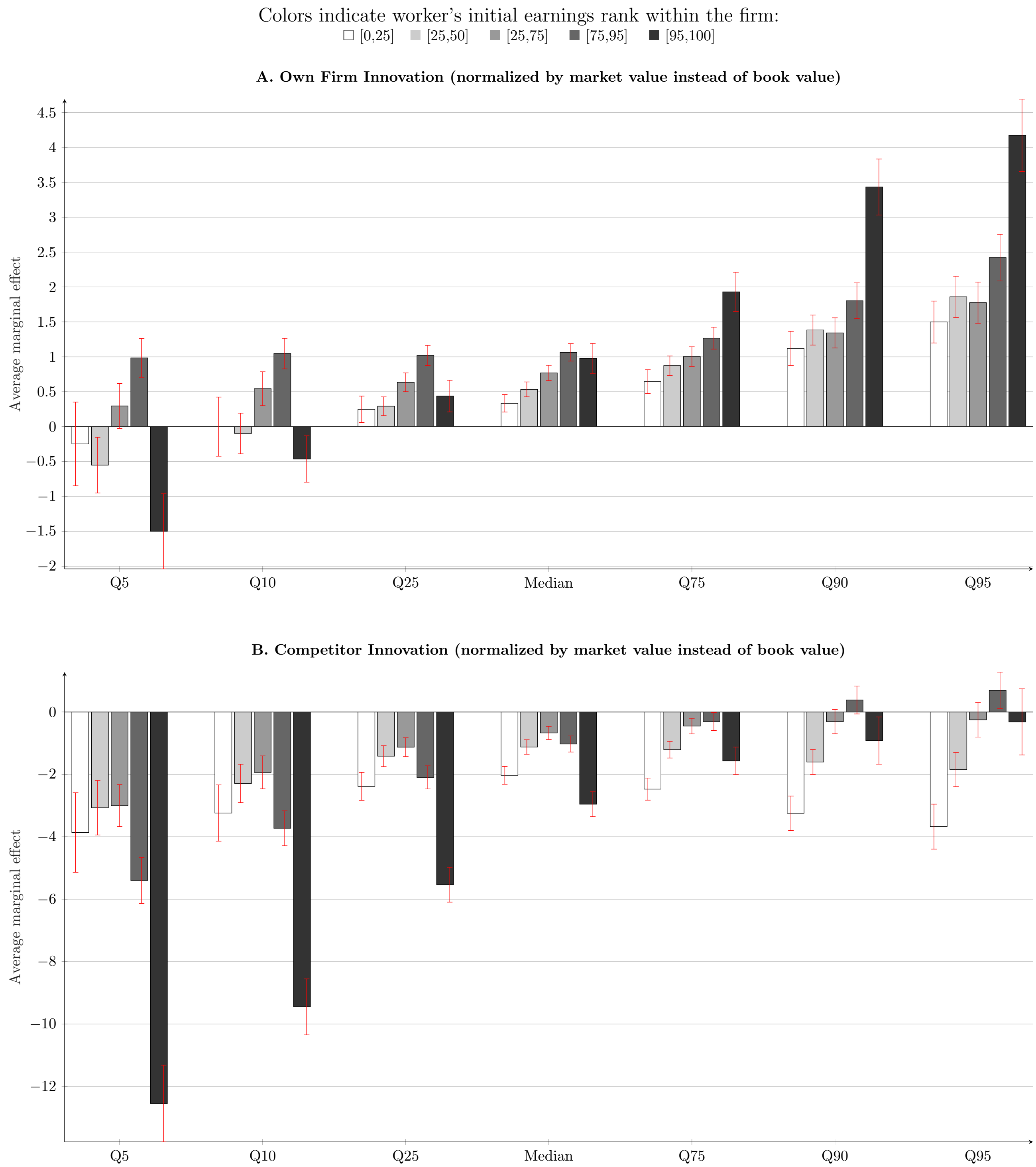
Note: Figure compares the average fitted quantiles plotted from Figure A.5 of the distribution of 5-year earnings growth for workers of different earnings levels (earnings ranks) with raw unconditional quantiles calculated for each group. Estimates are standardized to correspond with 1 standard deviation effects for each variable of interest. In addition to the specification which is estimated for the full sample, we also repeat the exercise separately for the subsamples of workers that remain with the same firm after 5 years (stayers) and for those that do not (movers). Stayers are defined as workers who are employed at the firm in year t+3; while movers workers who are not employed at the same firm in year t+3.

Figure A.15: Earnings growth and innovation conditional on earnings levels - control for R&D spending



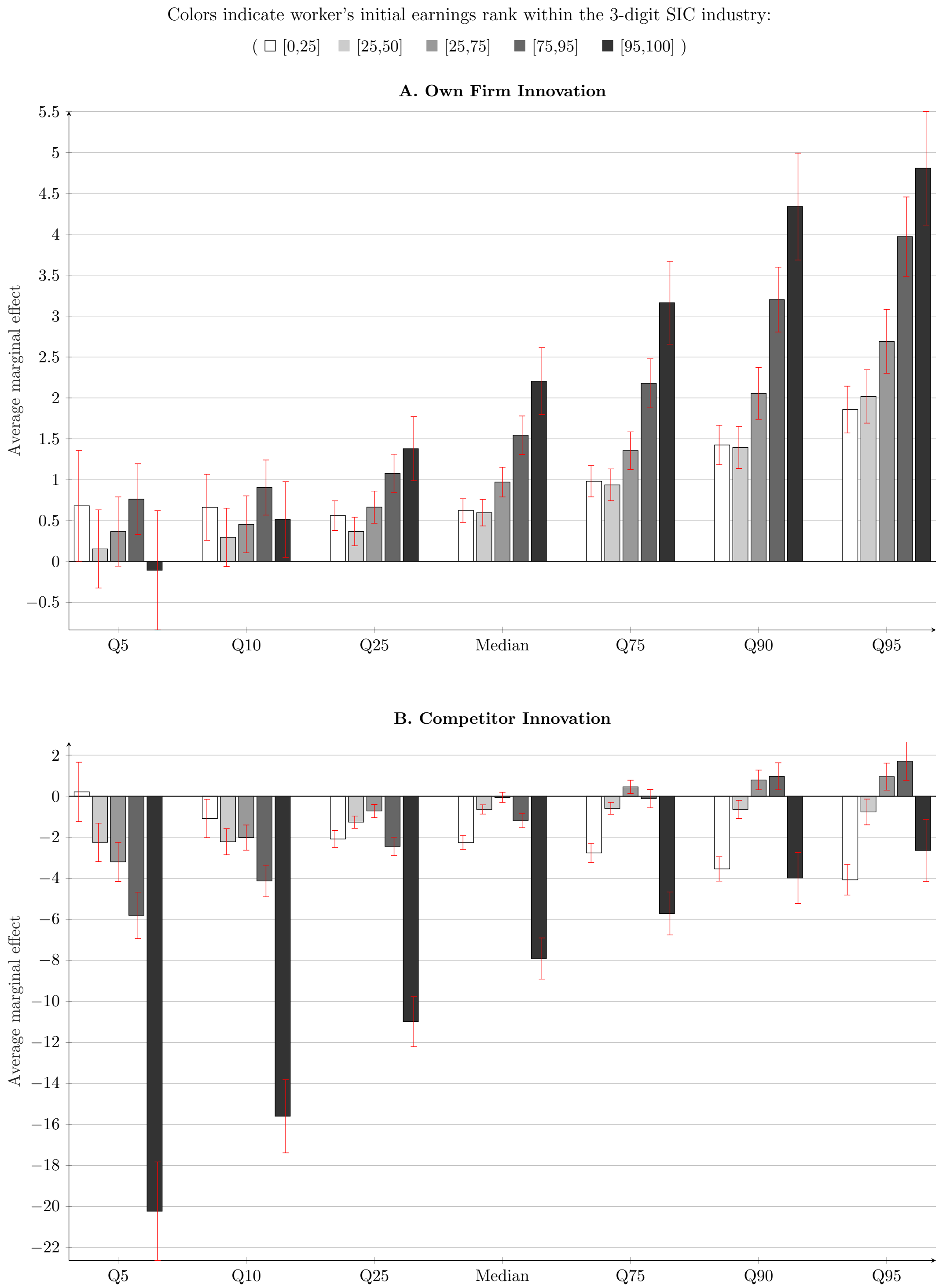
Note: Figure plots the average marginal effects of firm—and competitor—innovation that are implied by the quantile regression estimates (equation (12) in the main text) for workers with different earnings levels, where we additionally control for the ratio of R&D to assets in the regression (and drop firms with missing R&D data). Estimates are standardized to correspond with 1 standard deviation effects for each variable of interest. The worker earnings rank is defined net of deterministic life-cycle effects. We focus on 5-yr growth rates. The units on the vertical axis correspond to log points (times 100).

Figure A.16: Earnings growth and innovation conditional on earnings levels - alternative firm value scaling factor for innovation measure



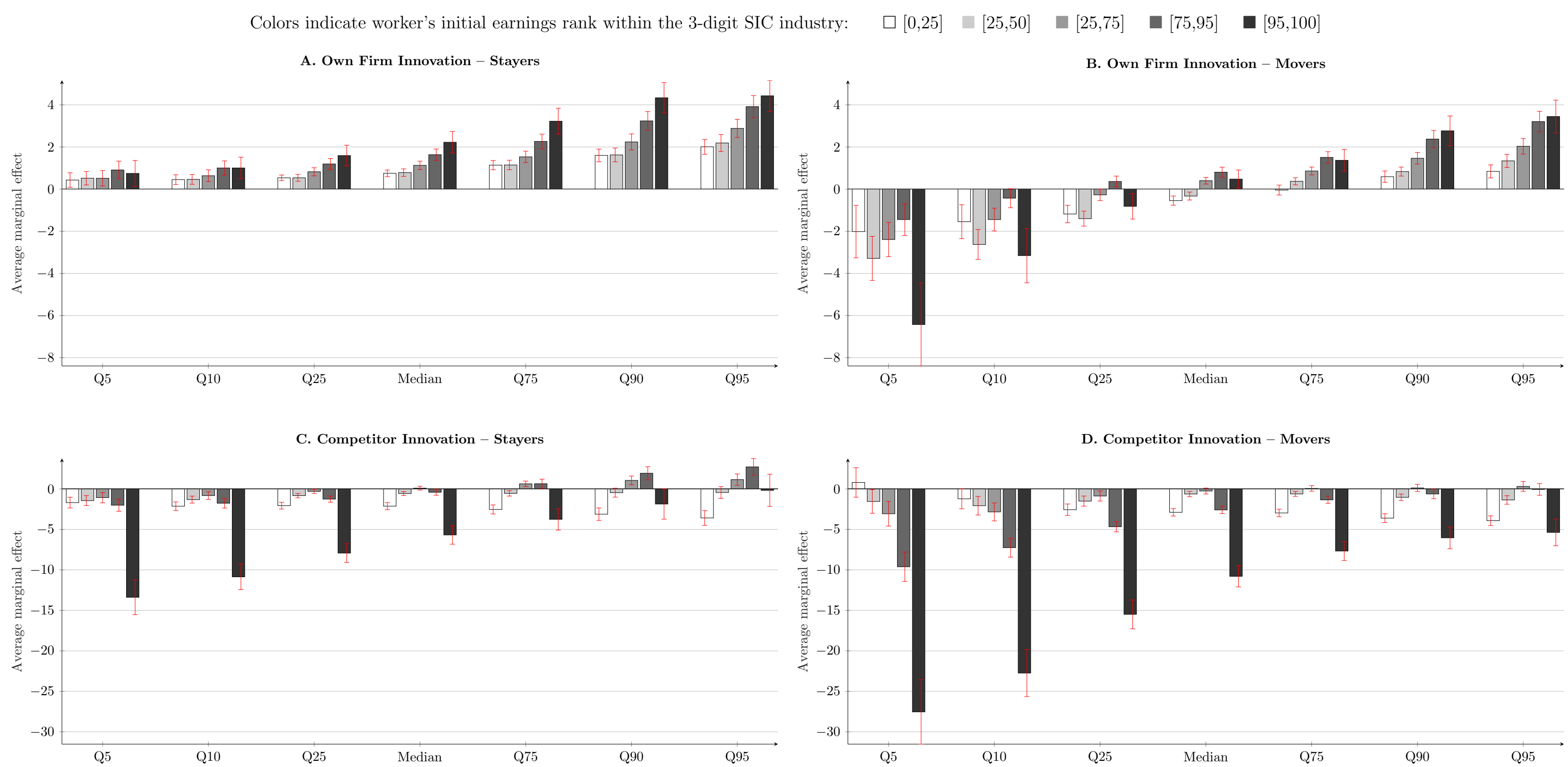
Note: Figure plots the average marginal effects of firm—and competitor—innovation that are implied by the quantile regression estimates (equation (12) in the main text) for workers with different earnings levels. Estimates are standardized to correspond with 1 standard deviation effects for each variable of interest. The difference from the baseline specification is that our innovation measure is scaled by the market value, rather than the book value, of firm assets. The worker earnings rank is defined net of deterministic life-cycle effects. We focus on 5-yr growth rates. The units on the vertical axis correspond to log points (times 100).

Figure A.17: Earnings growth and innovation conditional on earnings levels – sort on industry income rank



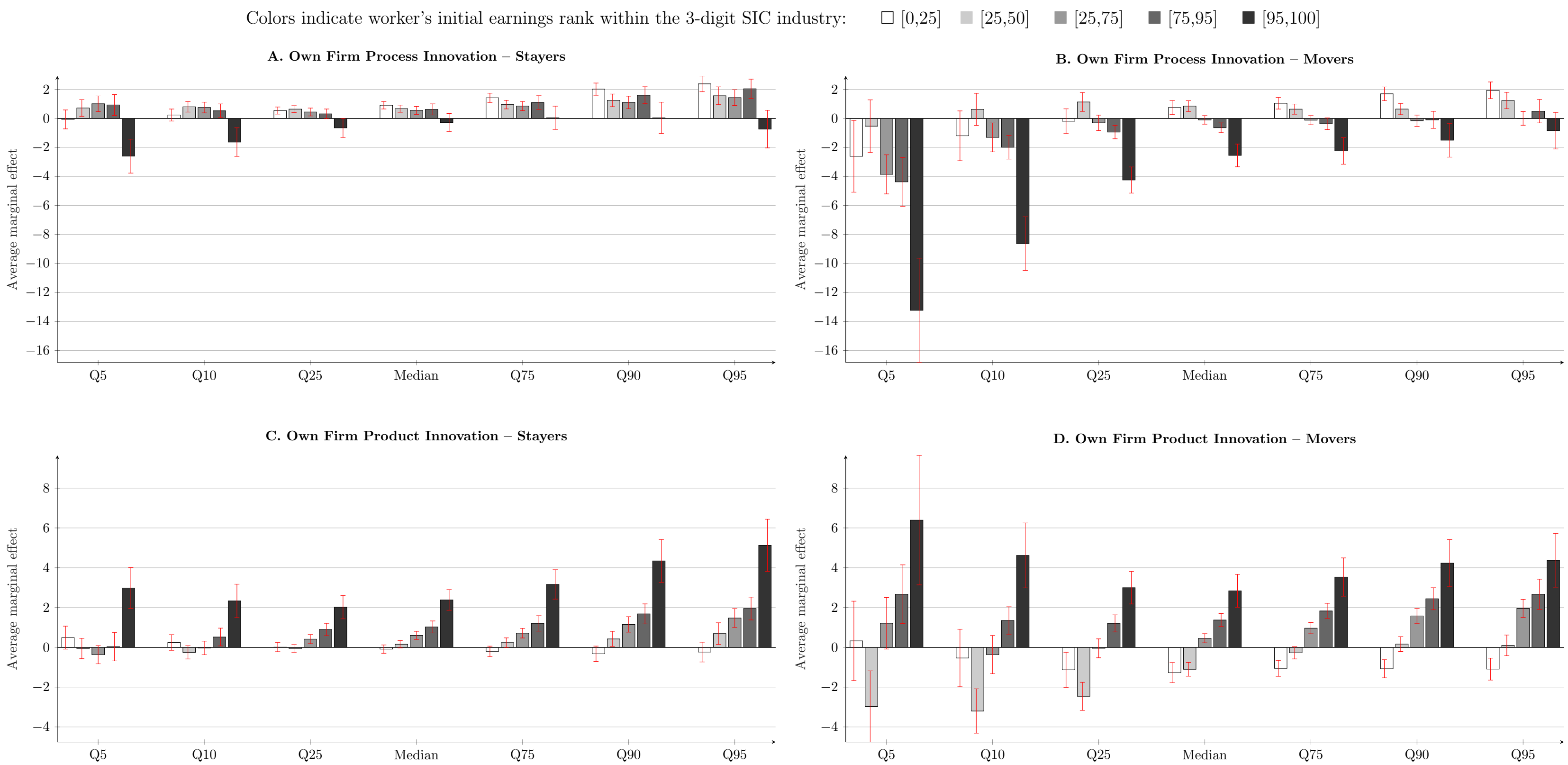
Note: Figure plots the average marginal effects of firm—and competitor—innovation that are implied by the quantile regression estimates (equation (12) in the main text) for workers with different earnings levels, where estimates are scaled to correspond with a 1 standard deviation change in each variable of interest. Whereas the baseline specification sorts on rank within the firm, here we compute ranks within the same 3-digit SIC industry. The worker earnings rank is defined net of deterministic life-cycle effects. We focus on 5-year growth rates. The units on the vertical axis correspond to log points (times 100).

Figure A.18: Earnings growth and innovation: movers versus continuing workers – sort on industry income rank



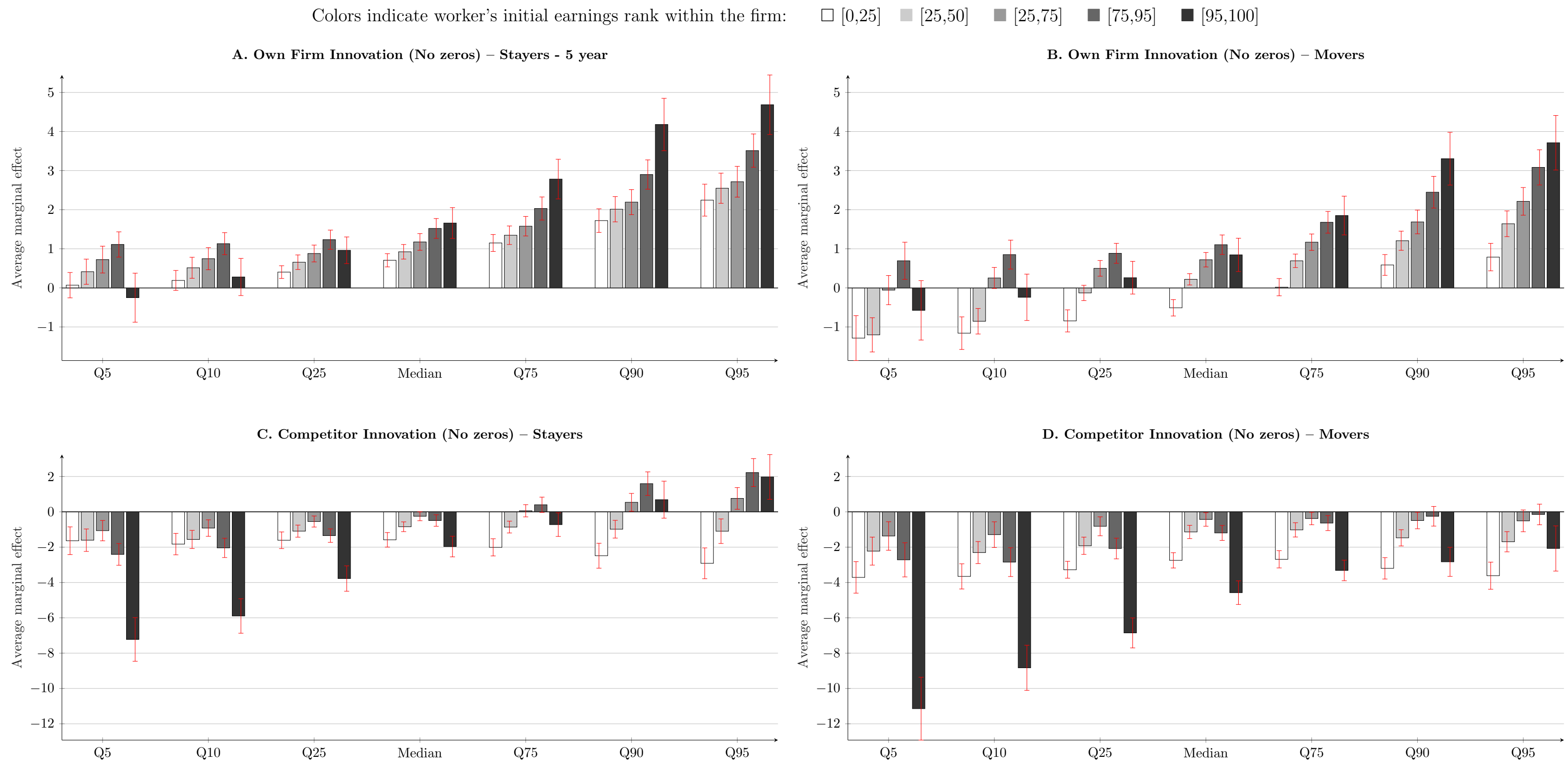
Note: Figure plots the average marginal effects of firm—and competitor—innovation that are implied by the quantile regression estimates (equation (12) in the main text) for workers with different earnings levels, where estimates are scaled to correspond with a 1 standard deviation change in each variable of interest. The equation is estimated separately for workers that remain with the firm (stayers) versus workers that leave the firm (switchers). Whereas the baseline specification sorts on rank within the firm, here we compute ranks within the same 3-digit SIC industry. The worker earnings rank is defined net of deterministic life-cycle effects. We focus on 5-year growth rates. The units on the vertical axis correspond to log points (times 100).

Figure A.19: Earnings growth and process/product innovation: movers versus continuing workers – sort on industry income rank



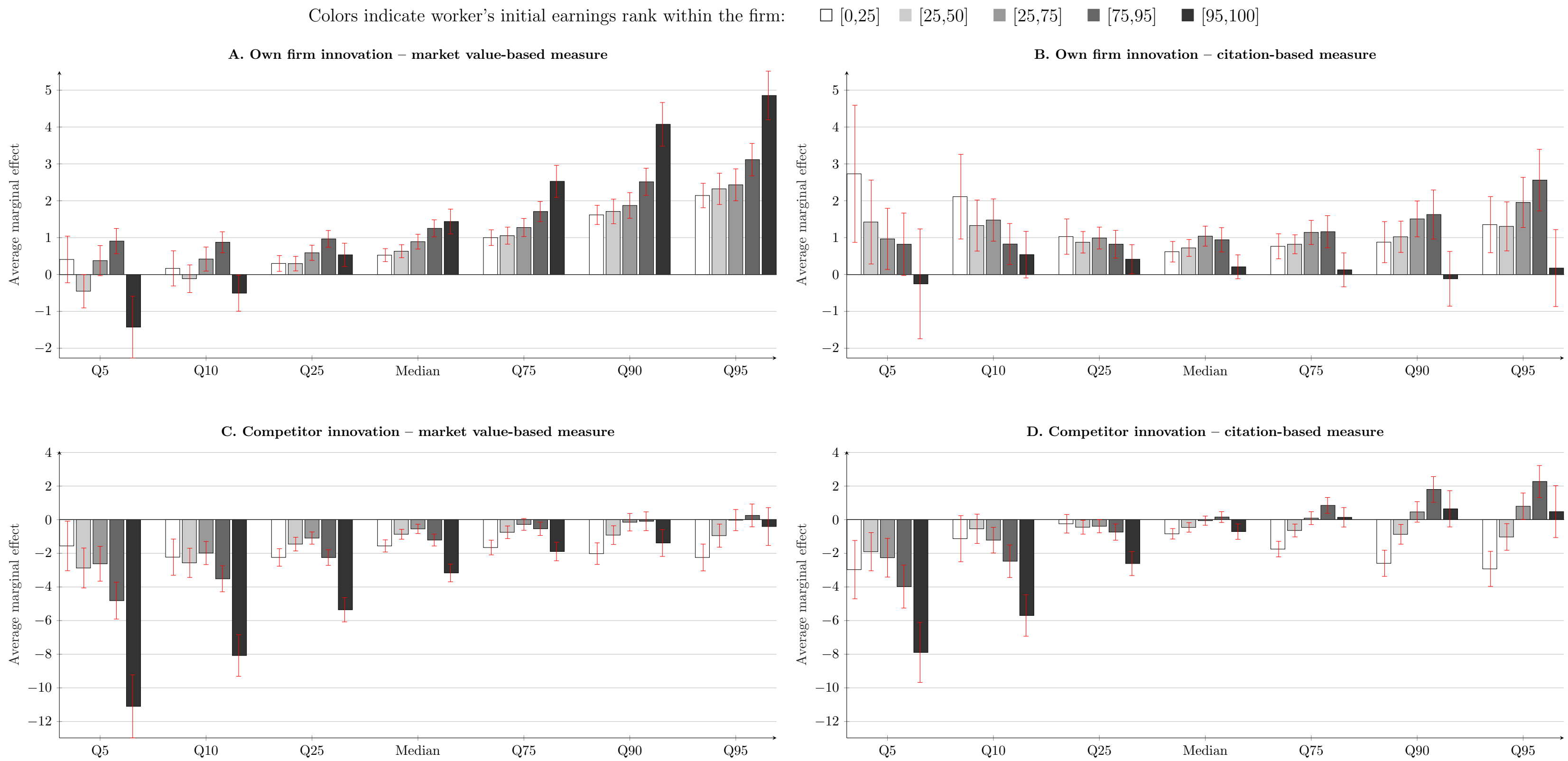
Note: Figure plots the average marginal effects of firm process/product innovation that are implied by the quantile regression estimates (equation (12) in the main text) for workers with different earnings levels, where estimates are scaled to correspond with a 1 standard deviation change in each variable of interest. The equation is estimated separately for workers that remain with the firm (stayers) versus workers that leave the firm (switchers). Whereas the baseline specification sorts on rank within the firm, here we compute ranks within the same 3-digit SIC industry. The worker earnings rank is defined net of deterministic life-cycle effects. We focus on 5-year growth rates. The units on the vertical axis correspond to log points (times 100).

Figure A.20: Earnings growth and innovation: movers versus continuing workers - exclude years with zero income obs



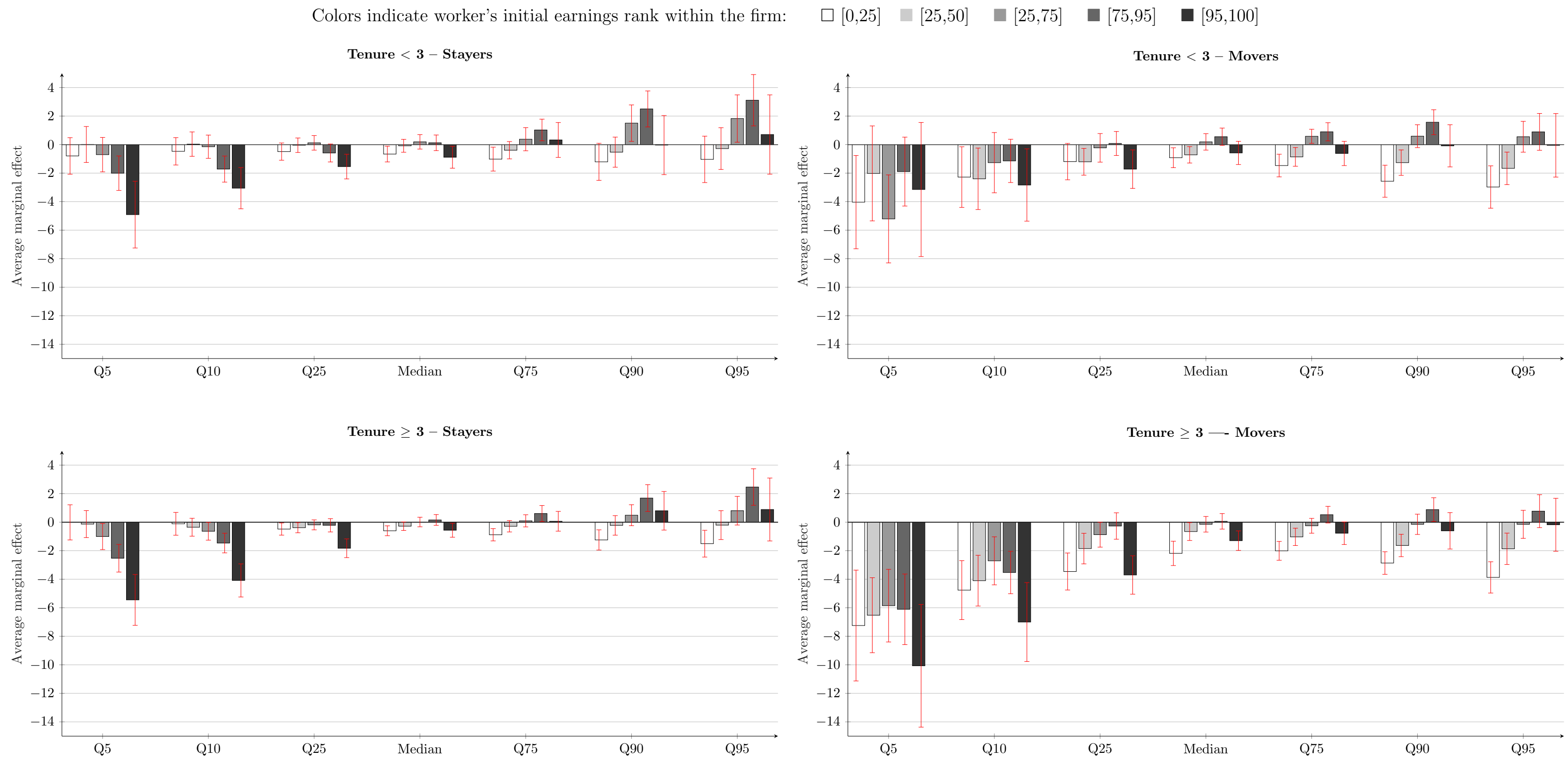
Note: Figure plots the average marginal effects of firm—and competitor—innovation that are implied by the quantile regression estimates (equation (12) in the main text) for workers with different earnings levels, where workers with any years with zero W-2 earnings are excluded from the estimation. Estimates are standardized to correspond with 1 standard deviation effects for each variable of interest. The equation is estimated separately for workers that remain with the firm (stayers) versus workers that leave the firm (switchers). The worker earnings rank is defined net of deterministic life-cycle effects. We focus on 5-yr growth rates. The units on the vertical axis correspond to log points (times 100).

Figure A.21: Earnings growth and innovation: valuable vs highly-cited patents



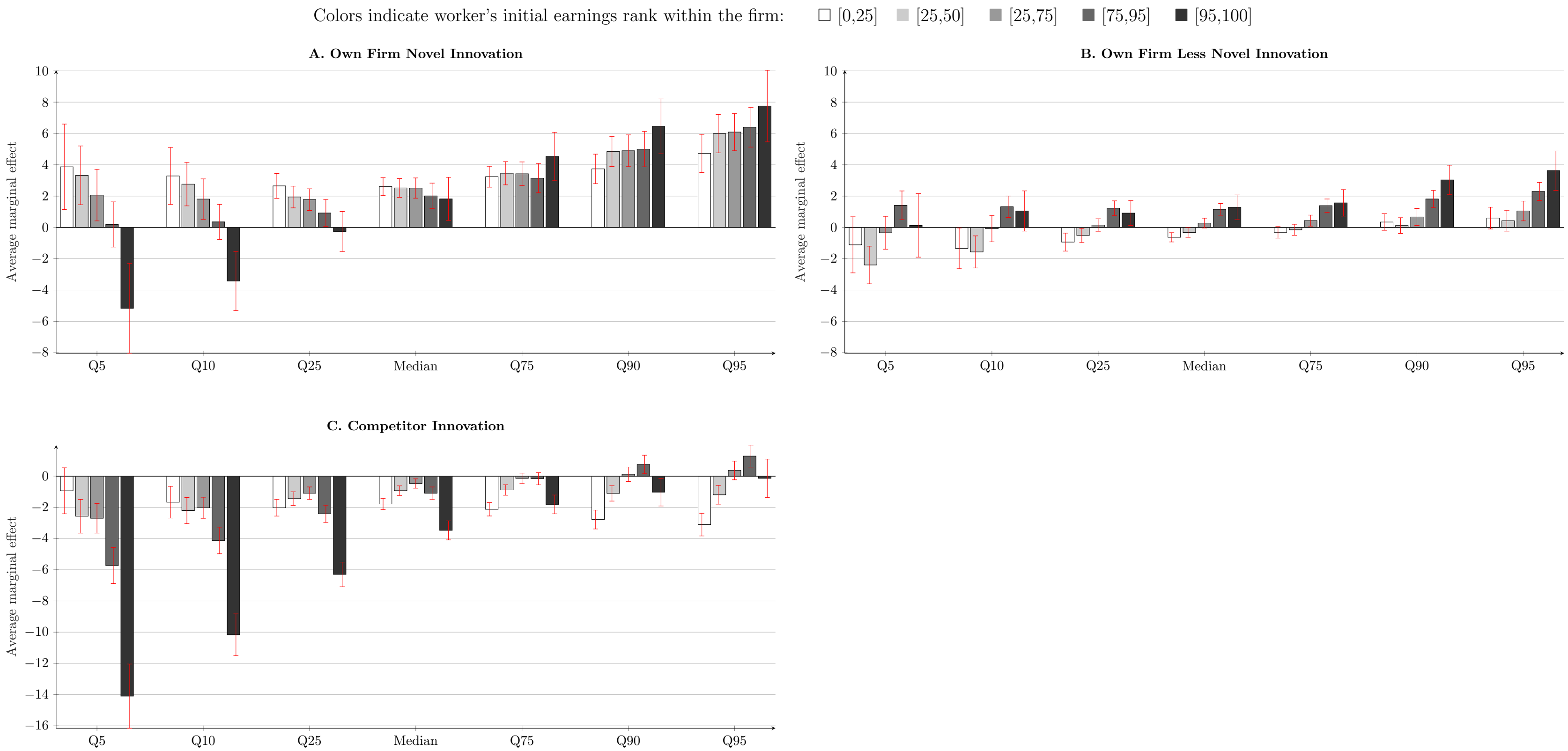
Note: Figure plots the average marginal effects of firm—and competitor—innovation that are implied by the quantile regression estimates (equation (12) in the main text) for workers with different earnings levels. In addition to using our market value-based measures of own firm and competitor innovation ($A^{sm}_{f,t}$ and $A^{sm}_{I\setminus f,t}$, respectively), we additionally include their citation-based analogs: $A^{cw}_{f,t}$ and $A^{cw}_{I\setminus f,t}$. Estimates are standardized to correspond with 1 standard deviation effects for each variable of interest. The equation is estimated separately for workers that remain with the firm (stayers) versus workers that leave the firm (switchers). The worker earnings rank is defined net of deterministic life-cycle effects. We focus on 5-yr growth rates. The units on the vertical axis correspond to log points (times 100).

Figure A.22: Earnings growth and competitor citation-weighted innovation conditional on worker earnings levels and tenure: movers versus continuing workers



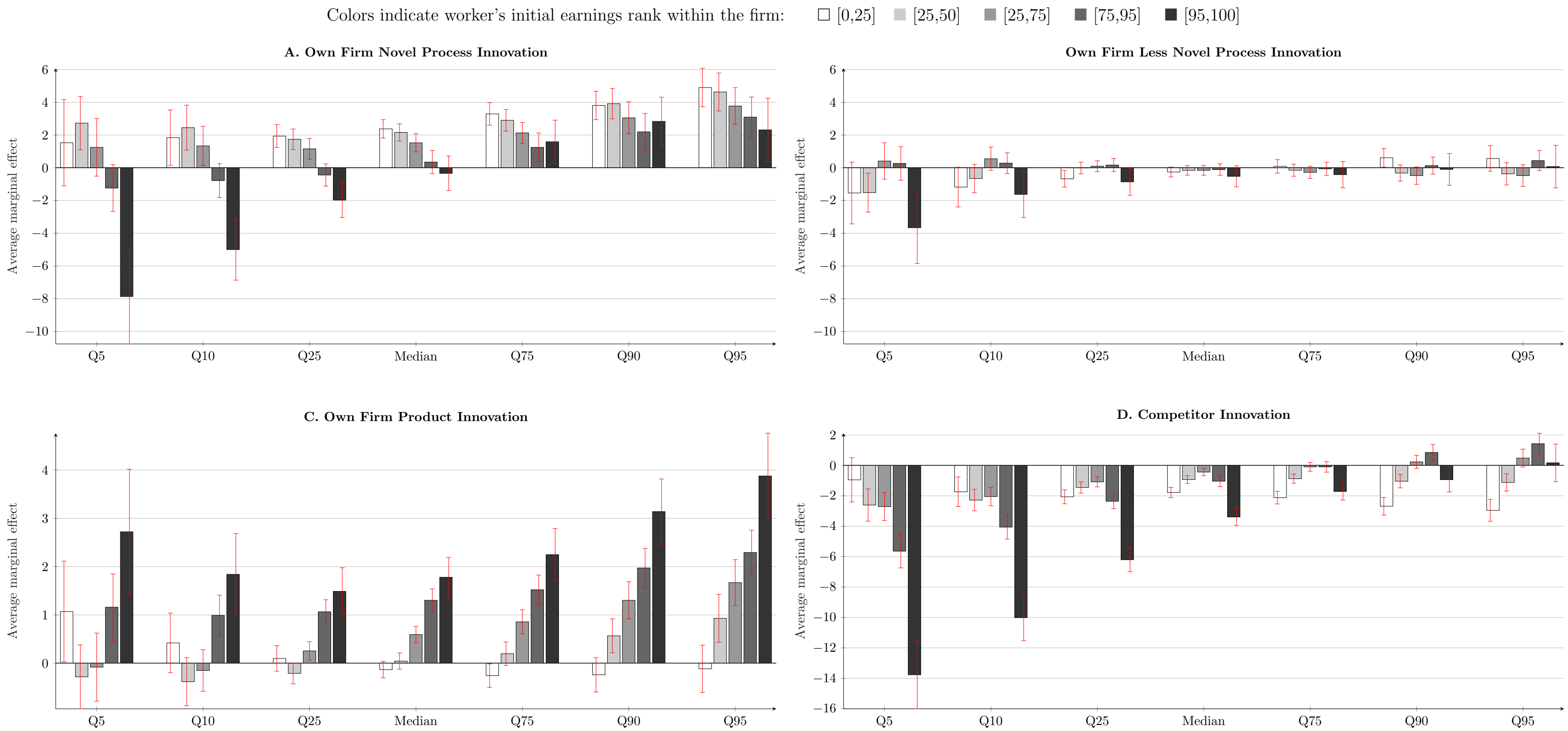
Note: Figure plots the average marginal effects of firm process innovation that are implied by the quantile regression estimates (equation (12) in the main text, except that we also include own-firm and competitor citation-based innovation measures) for workers with different earnings levels and and years of tenure with the firm. Workers are sorted into two groups based upon whether they have less than 3 years or greater than or equal to 3 years of tenure, and we allow for separate coefficients for each tenure × lagged earnings bin. Estimates are standardized to correspond with 1 standard deviation effects for each variable of interest. The equation is estimated separately for workers that remain with the firm (stayers) versus workers that leave the firm (switchers). The worker earnings rank is defined net of deterministic life-cycle effects. We focus on 5-yr growth rates. The units on the vertical axis correspond to log points (times 100).

Figure A.23: Earnings growth and innovation: responses to own firm high/low novelty and competitor innovation



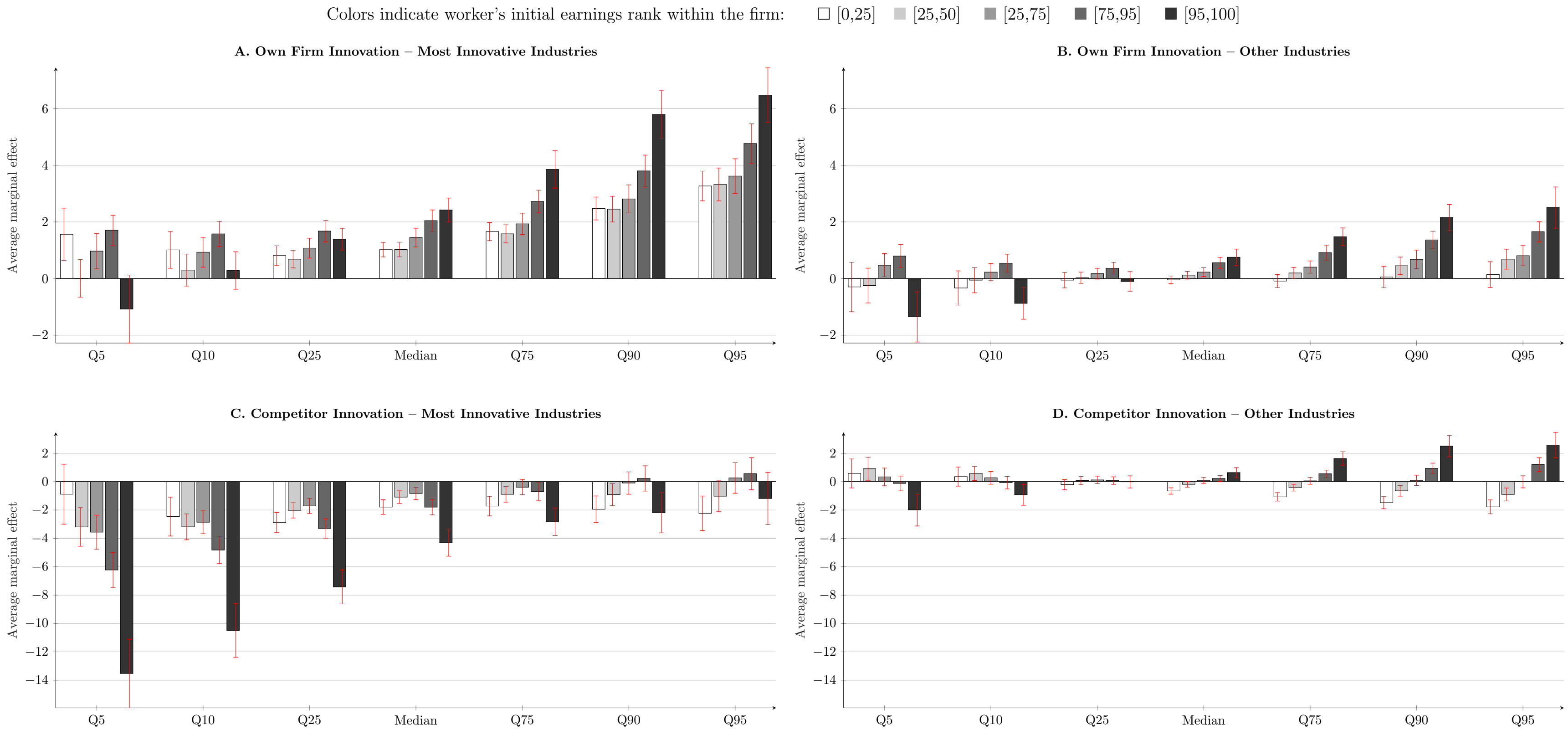
Note: Figure plots the average marginal effects of firm—and competitor—innovation that are implied by the quantile regression estimates (equation (12) in the main text) for workers with different earnings levels. Own firm innovation is separated into novel and less novel categories using the patent pairwise similarity measure of Kelly et al. (2020). A patent is classified as novel to the firm if its maximum similarity (cosine distance) to the firm's own prior patents is less than 0.5. The worker earnings rank is defined net of deterministic life-cycle effects. We focus on 5-yr growth rates. For ease of comparison, marginal effects for novel and less novel own firm innovation are scaled by the cross-sectional standard deviation of own firm innovation. Competitor innovation is scaled by its cross-sectional standard deviation. The units on the vertical axis correspond to log points (times 100).

Figure A.24: Earnings growth and innovation: responses to own firm high/low novelty process, product, and competitor innovation



Note: Figure plots the average marginal effects of firm—and competitor—innovation that are implied by the quantile regression estimates (equation (12) in the main text) for workers with different earnings levels. Each process patent is separated into novel and less novel categories using the patent pairwise similarity measure of Kelly et al. (2020). A patent is classified as novel to the firm if its maximum similarity (cosine distance) to the firm's own prior patents is less than 0.5. The worker earnings rank is defined net of deterministic life-cycle effects. For ease of comparison, marginal effects for novel and non-novel process innovation are scaled by the standard deviation of process innovation. Product innovation and competitor innovation measures are scaled by their cross-sectional standard deviations. We focus on 5-yr growth rates. The units on the vertical axis correspond to log points (times 100).

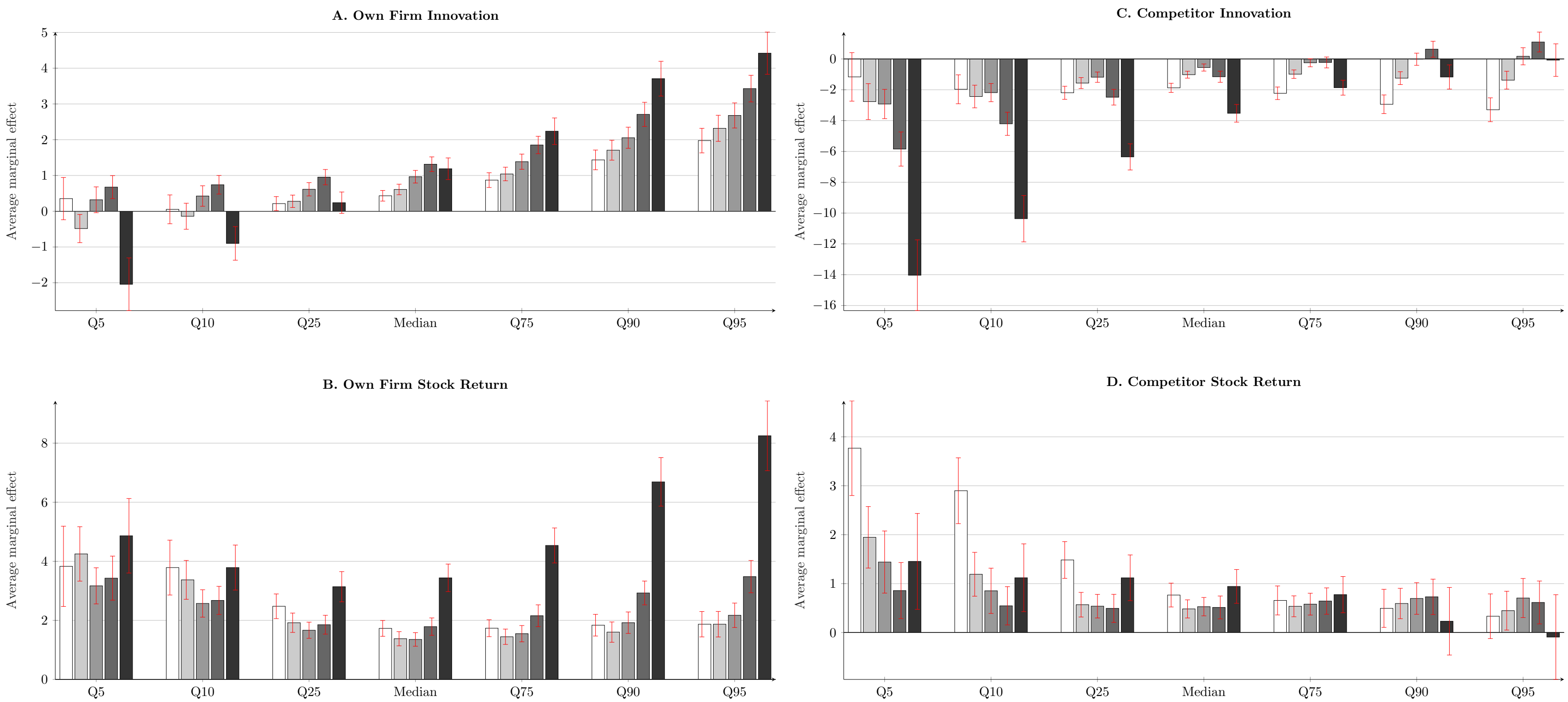
Figure A.25: Earnings growth and innovation conditional on worker earnings levels: most innovative versus other industries



Note: Figure plots the average marginal effects of own firm and competitor innovation that are implied by the quantile regression estimates (equation (12) in the main text) for workers with different earnings levels. The equation is estimated separately for workers in industries which are in the top tercile of innovativeness, which is defined as the average across years of the ratio of the market value of patents in each year (aggregated across firms within an industry year) divided by lagged book assets. We choose the breakpoint so that 1/3 of 3-digit SIC codes (weighted by Compustat employment) are included in the high-tech category. Estimates are standardized to correspond with 1 standard deviation effects for each variable of interest. The worker earnings rank is defined net of deterministic life-cycle effects. We focus on 5-yr growth rates. The units on the vertical axis correspond to log points (times 100).

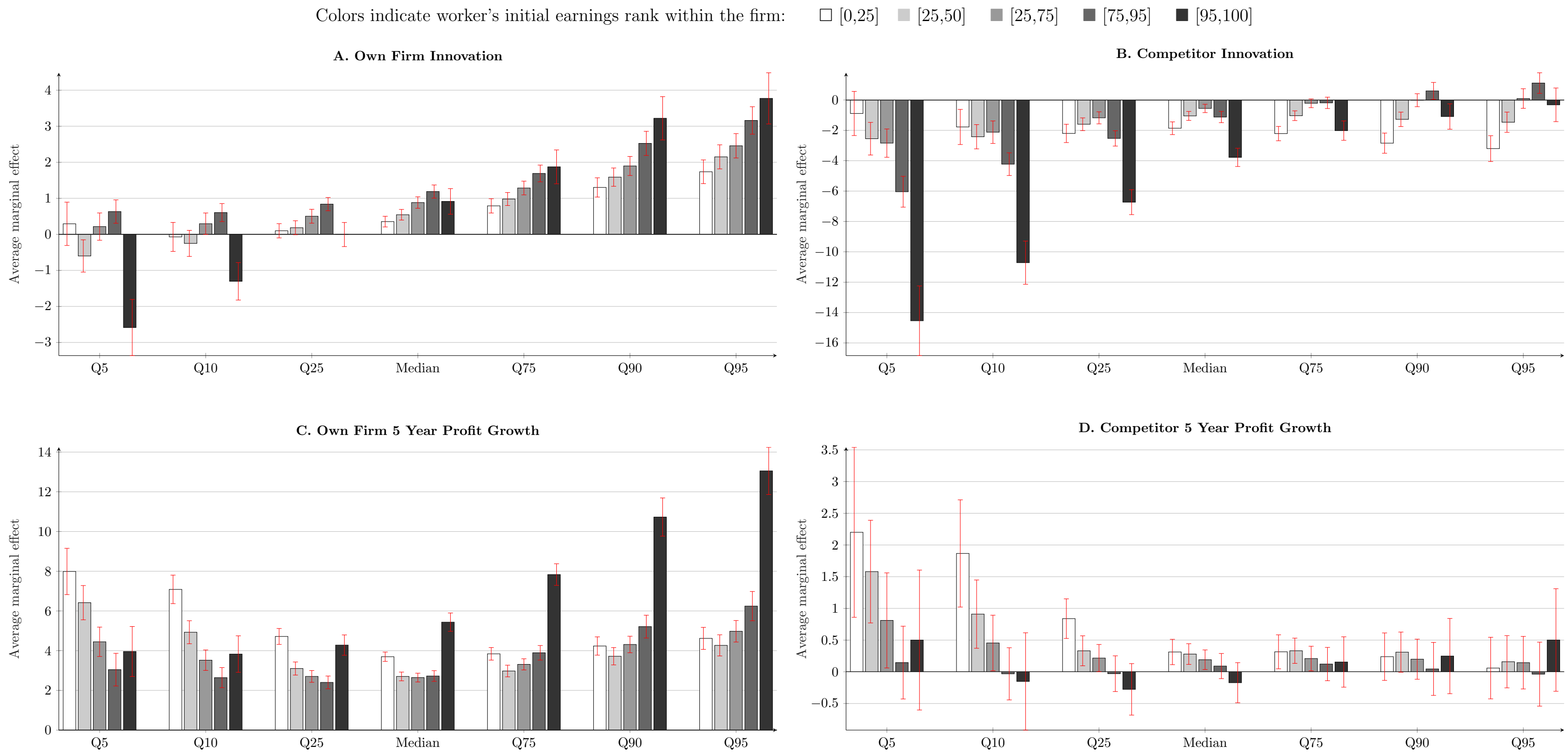
Figure A.26: Earnings growth and innovation: responses to own firm and competitor innovation, controlling for own/competitor stock returns

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



Note: Figure plots the average marginal effects of firm—and competitor—innovation that are implied by the quantile regression estimates (equation (12) in the main text) for workers with different earnings levels. In addition to the own firm and competitor innovation measures from the baseline specification, we also include controls for own firm and competitor 5 year cumulative profit growth and also allow these coefficients to vary with a worker's rank within the firm. Estimates are standardized to correspond with 1 standard deviation effects for each variable of interest. The worker earnings rank is defined net of deterministic life-cycle effects. We focus on 5-yr growth rates. The units on the vertical axis correspond to log points (times 100).

Figure A.27: Earnings growth and innovation: responses to own firm and competitor innovation, controlling for own/competitor profit growth



Note: Figure plots the average marginal effects of firm—and competitor—innovation that are implied by the quantile regression estimates (equation (12) in the main text) for workers with different earnings levels. In addition to the own firm and competitor innovation measures from the baseline specification, we also include controls for own firm and competitor stock returns and also allow these coefficients to vary with a worker's rank within the firm. Estimates are standardized to correspond with 1 standard deviation effects for each variable of interest. The worker earnings rank is defined net of deterministic life-cycle effects. We focus on 5-yr growth rates. The units on the vertical axis correspond to log points (times 100).

Table A.1: Worker descriptive statistics: matched sample

	Obs	Mean	SD	1%	5%	10%	25%	50%	75%	90%	95%	99%
Earnings (in thousands of 2013 dollars)	14,621,600	74.2	146.6	4.8	15.9	24.3	39.3	57.6	82.8	123.2	165.4	343.5
Age	14,621,600	39.6	8	26	27	29	33	39	46	51	53	54
Firm tenure	14,621,600	6.2	5.2	1	1	1	2	5	9	14	17	23
Firm tenure $\geq$ 3 years	14,621,600	0.7	0.4	0	0	0	0	1	1	1	1	1
Firm tenure $\geq$ 5 years	14,621,600	0.5	0.5	0	0	0	0	1	1	1	1	1
Cumulative 3 year log residual earnings growth	14,593,617	-0.07	0.59	-2.31	-0.88	-0.53	-0.17	-0.01	0.13	0.38	0.58	1.1
Cumulative 5 year log residual earnings growth	13,532,500	-0.09	0.61	-2.38	-0.96	-0.59	-0.21	-0.01	0.15	0.38	0.58	1.11
Cumulative 10 year log residual earnings growth	10,675,095	-0.12	0.65	-2.52	-1.09	-0.69	-0.28	-0.03	0.17	0.41	0.6	1.16
Left firm after 3 years	14,621,600	0.337	0.473	0	0	0	0	0	1	1	1	1
Number of years with zero earnings	13,823,082	0.142	0.566	0	0	0	0	0	0	0	1	3
Number of years with zero earnings, conditional on leaving firm after 3 years	4,661,544	0.327	0.875	0	0	0	0	0	0	1	3	4
Application for DI	11,128,626	0.026	0.159	0	0	0	0	0	0	0	0	1
Application for DI, conditional on leaving firm after 3 years	3,988,785	0.041	0.199	0	0	0	0	0	0	0	0	1

Note: Table reports univariate summary statistics for the sample of matched worker-level measures. The unit of analysis is the worker-year.

Table A.2: Worker descriptive statistics: Full versus matched sample

	Obs	Mean	SD	1%	5%	10%	25%	50%	75%	90%	95%	99%
Panel A. Matched sample												
Earnings (in thousands of 2013 dollars)	14,621,600	74.2	146.6	4.8	15.9	24.3	39.3	57.6	82.8	123.2	165.4	343.5
Age	14,621,600	39.6	8	26	27	29	33	39	46	51	53	54
Firm tenure	14,621,600	6.2	5.2	1	1	1	2	5	9	14	17	23
Firm tenure $\geq$ 3 years	14,621,600	0.7	0.4	0	0	0	0	1	1	1	1	1
Firm tenure $\geq$ 5 years	14,621,600	0.5	0.5	0	0	0	0	1	1	1	1	1
Cumulative 3 year log residual earnings growth	14,593,600	-0.07	0.59	-2.31	-0.88	-0.53	-0.17	-0.01	0.13	0.38	0.58	1.1
Cumulative 5 year log residual earnings growth	13,532,500	-0.09	0.61	-2.38	-0.96	-0.59	-0.21	-0.01	0.15	0.38	0.58	1.11
Cumulative 10 year log residual earnings growth	10,675,100	-0.12	0.65	-2.52	-1.09	-0.69	-0.28	-0.03	0.17	0.41	0.6	1.16
Left firm after 1 year	14,621,600	0.153	0.36	0	0	0	0	0	0	1	1	1
Left firm after 3 years	14,621,600	0.337	0.473	0	0	0	0	0	1	1	1	1
Number of years with zero earnings	13,823,100	0.142	0.566	0	0	0	0	0	0	0	1	3
Number of years with zero earnings, conditional on leaving firm after 3 years	4,661,500	0.327	0.875	0	0	0	0	0	0	1	3	4
Application for DI	11,128,600	0.026	0.159	0	0	0	0	0	0	0	0	1
Application for DI, conditional on leaving firm after 3 years	3,988,800	0.041	0.199	0	0	0	0	0	0	0	0	1
Panel B. SSA worker sample (based on 10% sample)												
	Obs	Mean	SD	1%	5%	10%	25%	50%	75%	90%	95%	99%
Earnings (in thousands of 2013 dollars)	110927670	58.2	124.1	2.7	7.8	13.8	26.5	43.4	66	100.3	138.2	313.5
Age	104,030,810	38.9	8.1	26	27	28	32	38	46	51	52	54
Firm tenure	110,758,800	5.1	4.7	1	1	1	2	3	7	12	15	21
Firm tenure $\geq$ 3 years	110,758,800	0.6	0.5	0	0	0	0	1	1	1	1	1
Firm tenure $\geq$ 5 years	110,758,800	0.4	0.5	0	0	0	0	0	1	1	1	1
Cumulative 3 year log residual earnings growth	103,627,700	-0.09	0.65	-2.63	-1.09	-0.64	-0.21	-0.01	0.15	0.43	0.66	1.27
Cumulative 5 year log residual earnings growth	93,147,900	-0.1	0.67	-2.69	-1.15	-0.69	-0.25	-0.02	0.17	0.44	0.67	1.3
Cumulative 10 year log residual earnings growth	68,598,500	-0.12	0.71	-2.8	-1.26	-0.77	-0.3	-0.02	0.19	0.47	0.71	1.38
Left firm after 1 year	110,535,700	0.249	0.432	0	0	0	0	0	0	1	1	1
Left firm after 3 years	110,013,200	0.454	0.498	0	0	0	0	0	1	1	1	1
Number of years with zero earnings	101,607,000	0.248	0.792	0	0	0	0	0	0	1	2	4
Number of years with zero earnings, conditional on leaving firm after 3 years	46,355,400	0.467	1.085	0	0	0	0	0	0	2	3	5
Application for DI	88,363,000	0.031	0.173	0	0	0	0	0	0	0	0	1
Application for DI, conditional on leaving firm after 3 years	39,136,500	0.048	0.213	0	0	0	0	0	0	0	0	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 worker-year. Sample sizes have been rounded to the nearest 100.

Table A.3: Firm descriptive statistics: matched vs non-matched sample

	Obs	Mean	SD	1%	5%	10%	25%	50%	75%	90%	95%	99%
A. Matched sample												
	Obs	Mean	SD	1%	5%	10%	25%	50%	75%	90%	95%	99%
Employment (1000s)	117,300	8.42	36.88	0.01	0.02	0.05	0.17	0.79	4	16.5	37.9	128.9
Employment (SSA, 1000s)	119,900	3.77	16.34	0	0.01	0.02	0.08	0.34	1.7	7.0	16.0	59.2
Book assets, log	119,900	4.87	2.24	0.46	1.4	2.0	3.3	4.7	6.4	7.9	8.8	10.3
Return on assets	119,500	-0.01	0.28	-1.31	-0.55	-0.27	-0.01	0.07	0.12	0.17	0.2	0.29
R&D to assets	73,600	0.09	0.14	0	0	0	0.01	0.04	0.11	0.23	0.37	0.75
Firm volatility	110,600	-3.4	0.56	-4.54	-4.29	-4.13	-3.81	-3.41	-3.02	-2.65	-2.44	-2.05
Firm stock return	118,600	0.14	0.74	-0.86	-0.68	-0.54	-0.27	0.03	0.37	0.85	1.34	2.85
Industry stock return	118,300	0.13	0.29	-0.51	-0.33	-0.21	-0.05	0.12	0.29	0.47	0.62	0.9
Firm innovation	119,900	0.06	0.24	0	0	0	0	0	0.01	0.12	0.31	1.12
Firm innovation, non-process	119,900	0.03	0.13	0	0	0	0	0	0	0.06	0.17	0.64
Firm innovation, process	119,900	0.02	0.08	0	0	0	0	0	0	0.03	0.09	0.39
Competitor innovation	119,900	0.15	0.27	0	0	0	0	0.04	0.19	0.43	0.7	1.19
B. Non-Matched sample												
	Obs	Mean	SD	1%	5%	10%	25%	50%	75%	90%	95%	99%
Employment (1000s)	24,900	5.84	30.6	0	0	0.02	0.11	0.63	2.8	9.9	21.8	108.8
Book assets, log	25,900	4.89	2.19	0.4	1.4	2	3.3	4.9	6.4	7.7	8.6	10.2
Return on assets	25,700	-0.02	0.29	-1.31	-0.57	-0.28	-0.02	0.06	0.11	0.17	0.21	0.31
R&D to assets	12,200	0.08	0.14	0	0	0	0	0.02	0.09	0.22	0.35	0.76
Firm volatility	19,500	-3.28	0.56	-4.51	-4.18	-3.99	-3.68	-3.3	-2.9	-2.53	-2.33	-1.94
Firm stock return	25,500	0.1	0.71	-0.87	-0.72	-0.59	-0.31	0	0.33	0.82	1.33	2.67
Industry stock return	25,300	0.11	0.27	-0.51	-0.33	-0.21	-0.05	0.11	0.26	0.43	0.59	0.86
Firm innovation	25,900	0.01	0.11	0	0	0	0	0	0	0	0.03	0.34
Firm innovation, non-process	25,900	0.01	0.05	0	0	0	0	0	0	0	0.01	0.15
Firm innovation, process	25,900	0	0.04	0	0	0	0	0	0	0	0	0.09
Competitor innovation	25,900	0.1	0.2	0	0	0	0	0.01	0.13	0.29	0.43	1.07

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. Sample sizes have been rounded to the nearest 100.

Table A.4: Earnings growth and own/competitor innovation, stock returns, and profit growth conditional on earnings levels: OLS estimates

A. Innovation						
Variable	Scaling	Earnings rank				
		[0,25]	[25,50]	[50,75]	[75,95]	[95,100]
Innovation by the firm, A_f	StdDev	1.19	1.09	1.40	1.85	1.53
	Elasticity	0.149	0.137	0.176	0.231	0.191
		[10.86]	[8.07]	[9.98]	[14.41]	[8.34]
Innovation by competitors, $A_{I\setminus f}$	StdDev	-1.92	-1.40	-1.01	-2.20	-5.92
	Elasticity	0.39	0.284	0.204	0.444	1.201
		[-6.41]	[-5.68]	[-3.91]	[-6.87]	[-11.9]

B. Stock returns						
Variable	Scaling	Earnings rank				
		[0,25]	[25,50]	[50,75]	[75,95]	[95,100]
Own firm stock return, R_f	Elasticity	0.0355	0.0314	0.0306	0.0403	0.0673
		[15.21]	[15.91]	[13.66]	[14.07]	[11.85]
Competitor stock return, $R_{I\setminus f}$	Elasticity	0.0570	0.0236	0.0218	0.0238	0.0485
		[7.26]	[3.99]	[4.11]	[3.29]	[3.06]

C. Profit growth over the next 5 years						
Variable	Scaling	Earnings rank				
		[0,25]	[25,50]	[50,75]	[75,95]	[95,100]
Own firm profit growth,	Elasticity	0.0921	0.0706	0.0672	0.0728	0.1283
$\log\left[\frac{1}{\lvert 5\rvert}\sum_{\tau=1}^{5} X_{f,t+\tau}\right] - \log X_{f,t}$		[33.129]	[28.016]	[26.047]	[18.909]	[17.456]
Competitor profit growth	Elasticity	0.0092	0.0049	0.0023	0.0002	0.0021
$\log\left[\frac{1}{\lvert 5\rvert}\sum_{\tau=1}^{5} X_{I\setminus f,t+\tau}\right] - \log X_{f,t}$		[5.274]	[3.829]	[1.513]	[0.119]	[0.814]

Note: Table plots the average marginal effects of firm—and competitor—innovation that are implied by OLS estimates of equation (12) in the main text, where we allow for heterogenous coefficients for workers with different earnings levels. In panel A, we use our baseline own and competitor innovation measures, and estimates are scaled to correspond with a 1 standard deviation changes in each (analogous to Figure 4 in the main text). We additionally report the ratio of these coefficients to the firm-level slope coefficients from Table 1. In panels B and C, we report coefficients for analogous specifications where we use own firm and competitor stock returns and 5 year cumulative profit growth, respectively. The worker earnings rank is defined net of deterministic life-cycle effects. We focus on 5-year growth rates. The units on the vertical axis correspond to log points (times 100).

Table A.5: Worker mobility following innovation

Dependent variable: Indicator for leaving the firm within 3 years ($\times$100)					
i. Innovation	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)
ii. Stock return	Worker earnings rank				
	[0,25]	[25,50]	[50,75]	[75,95]	[95,100]
Firm stock return, R_f	-2.33	-2.48	-2.71	-2.94	-3.31
	(-15.08)	(-15.84)	(-17.47)	(-17.83)	(-18.99)
Competitor stock return, $R_{I\setminus f}$	-0.14	0.15	0.32	0.67	0.91
	(-0.97)	(1.06)	(2.20)	(4.49)	(5.61)

Note: This table reports point estimates of OLS regressions of equation (14) in the paper. The dependent variable is a dummy which equals 1 if, at $t+3$, a worker is no longer employed at the same firm as at time t ($\times$100). We allow the coefficients on innovation to vary across workers with different earnings ranks, which are defined net of deterministic life-cycle effects. The coefficients are standardized to a unit-standard deviation shock in the independent variable. Standard errors, in parentheses, are clustered at the firm level. Panel A is the same as Table 2 in the paper, and is included for comparison. In Panel B, we replace the firm and competitor innovation measures with their stock returns (in a direct analogue to Figure 7).

Table A.6: Earnings growth and own/competitor innovation or stock returns conditional on earnings levels and mobility status: OLS estimates

A. Innovation							
Variable	Mobility Status	Scaling	Earnings rank				
			[0,25]	[25,50]	[50,75]	[75,95]	[95,100]
Innovation by the firm, A_f	Overall	StdDev	1.19	1.09	1.40	1.85	1.53
		Elasticity	0.149	0.137	0.176	0.231	0.191
			[10.86]	[8.07]	[9.98]	[14.41]	[8.34]
	Stayer	StdDev	1.08	1.38	1.61	2.08	2.16
		Elasticity	0.135	0.173	0.201	0.261	0.271
			[7.48]	[9.79]	[10.46]	[14.07]	[9.22]
	Switcher	StdDev	-0.28	-0.23	0.38	0.75	-1.04
		Elasticity	-0.035	-0.028	0.047	0.093	-0.13
			[-1.92]	[-1.5]	[3.11]	[4.97]	[-2.65]
Innovation by competitors, $A_{I\setminus f}$	Overall	StdDev	-1.92	-1.40	-1.01	-2.20	-5.92
		Elasticity	0.39	0.284	0.204	0.444	1.201
			[-6.41]	[-5.68]	[-3.91]	[-6.87]	[-11.9]
	Stayer	StdDev	-2.07	-1.37	-0.60	-1.22	-4.21
		Elasticity	0.419	0.279	0.122	0.248	0.854
			[-6.39]	[-6.12]	[-3.11]	[-5]	[-8.76]
	Switcher	StdDev	-1.90	-1.31	-1.25	-3.05	-7.99
		Elasticity	0.385	0.266	0.253	0.618	1.622
			[-6.82]	[-5.22]	[-5.06]	[-8.18]	[-13.18]

B. Stock returns							
Variable	Mobility Status	Scaling	Earnings rank				
			[0,25]	[25,50]	[50,75]	[75,95]	[95,100]
Own firm stock return, R_f	Overall	Elasticity	0.0355	0.0314	0.0306	0.0403	0.0673
			[15.21]	[15.91]	[13.66]	[14.07]	[11.85]
	Stayer	Elasticity	0.0328	0.0293	0.0323	0.0427	0.0686
			[13.17]	[13.49]	[12.05]	[14.48]	[13.1]
	Switcher	Elasticity	0.0113	0.0129	0.0106	0.018	0.042
			[2.94]	[4.65]	[4.41]	[5.77]	[6.19]
Competitor stock return, $R_{I\setminus f}$	Overall	Elasticity	0.0570	0.0236	0.0218	0.0238	0.0485
			[7.26]	[3.99]	[4.11]	[3.29]	[3.06]
	Stayer	Elasticity	0.0128	0.0088	0.0122	0.0193	0.0532
			[2.13]	[1.96]	[2.76]	[3.02]	[4.11]
	Switcher	Elasticity	0.0775	0.038	0.0351	0.0389	0.0509
			[9.03]	[4.6]	[4.35]	[3.94]	[1.99]

Note: Table plots the average marginal effects of firm—and competitor—innovation that are implied by OLS estimates of equation (12) in the main text, where we allow for heterogenous coefficients for workers with different earnings levels. We also report estimates where the equation is estimated separately for workers that remain with the firm (stayers) versus workers that leave the firm (switchers). In panel A, we use our baseline own and competitor innovation measures, and estimates are scaled to correspond with a 1 standard deviation changes in each (analogous to Figure 4 in the main text). We additionally report the ratio of these coefficients to the firm-level slope coefficients from Table 1 ('elasticity'). In panel B, we report coefficients for analogous specifications where we replace the innovation measures with own firm and competitor stock returns. The worker earnings rank is defined net of deterministic life-cycle effects. We focus on 5-year growth rates. The units on the vertical axis correspond to log points (times 100).

Table A.7: Innovation and long-term unemployment

A. Number of years unemployed (×100), 5yr horizon					
Innovation	Worker earnings rank				
	[0,25]	[25,50]	[50,75]	[75,95]	[95,100]
Innovation by the firm, A_f	-0.28	0.55	0.43	0.61	1.06
	[-2.58]	[6.32]	[4.96]	[4.40]	[5.44]
Innovation by competitors, $A_{I\setminus f}$	-0.73	0.49	1.42	2.07	2.17
	[-3.55]	[3.08]	[9.20]	[10.33]	[8.36]

B. Application for disability insurance (DI) indicator (×100), 5yr horizon					
Innovation	Worker earnings rank				
	[0,25]	[25,50]	[50,75]	[75,95]	[95,100]
Innovation by the firm, A_f	-0.11	0.02	0.04	0.05	0.08
	[-6.56]	[1.46]	[3.92]	[6.03]	[7.05]
Innovation by competitors, $A_{I\setminus f}$	-0.35	-0.16	0.02	0.18	0.19
	[-8.70]	[-5.41]	[0.76]	[7.35]	[5.87]

Note: This table reports a modified version of Table 2 in the paper, in which the dependent variables are defined unconditionally, that is, we are not conditioning on whether the worker has left the firm. Specifically, Panel A reports OLS estimates of equation (15) in the paper. The dependent variable is a count of the number of years of zero W2 earnings worker i has experienced between years $t+1$ and $t+5$ (×100). Panel B reports estimates of equation (16) in the paper. The dependent variable is a dummy that takes the value of 1 if worker i has applied for disability insurance at any point between years $t+1$ and $t+5$ (×100). In both cases, we allow the response of the dependent variable to innovation (by the firm A_f or its competitors $A_{I\setminus f}$) to vary based on the worker's earnings rank, which are defined net of deterministic life-cycle effects. The coefficients are standardized to a unit-standard deviation shock in the independent variable. Standard errors, in parentheses, are clustered at the firm level.

Table A.8: Innovation and long-term unemployment: process vs non-process

A. Number of years unemployed (× 100), 5yr horizon (conditional on having left firm within 3 yrs)

Innovation	Earnings rank				
	[0,25]	[25,50]	[50,75]	[75,95]	[95,100]
Firm Process	3.41	3.19	3.62	4.33	6.23
	[3.00]	[3.36]	[4.05]	[4.07]	[3.92]
Firm Non-process	-0.82	1.44	0.79	1.02	2.34
	[-1.25]	[2.49]	[1.61]	[1.81]	[2.56]
Innovation by competitors, $A_{I\setminus f}$	-0.4	1.28	2.95	3.92	3.86
	[-1.17]	[4.51]	[10.37]	[11.01]	[8.17]

B. Application for disability insurance (DI) indicator (× 100), 5yr horizon (conditional on having left firm within 3 yrs)

Innovation	Earnings rank				
	[0,25]	[25,50]	[50,75]	[75,95]	[95,100]
Process innovation by the firm	-0.47	-0.04	0.12	0.34	0.15
	[-2.32]	[-0.34]	[1.50]	[5.56]	[1.50]
Other innovation by the firm	0.17	0.11	0.05	-0.04	0.10
	[1.31]	[1.29]	[0.98]	[-1.08]	[1.64]
Innovation by competitors, $A_{I\setminus f}$	-0.37	-0.16	0.1	0.32	0.37
	[-6.13]	[-3.28]	[2.55]	[8.13]	[6.87]

Note: This table reports a extension of the results reported in Table 2 in the paper, in which we decompose the firm innovation measure into process and non-process, in a manner analogous to the results in Figure 6. Panel A reports OLS estimates of equation (15) in the paper. The dependent variable is a count of the number of years of zero W2 earnings worker i has experienced between years $t+1$ and $t+5$. Panel B reports estimates of equation (16) in the paper. The dependent variable is a dummy that takes the value of 1 if worker i has applied for disability insurance at any point between years $t+1$ and $t+5$. In both cases, we allow the response of the dependent variable to innovation (by the firm A_f or its competitors $A_{I\setminus f}$) to vary based on the worker's earnings rank, which are defined net of deterministic life-cycle effects. For ease of comparison of magnitudes, coefficients on both types of own-firm innovation are standardized to a unit-standard deviation shock in A_f (overall firm innovation), expressed in percentage points (times 100), and coefficients on competitor innovation are scaled by the cross-sectional standard deviation of the competitor innovation measure. Standard errors, in parentheses, are clustered at the firm level.

Table A.9: Innovation and long-term unemployment: by worker tenure

A. Probability of leaving the firm within 3 years						
Innovation	Tenure	Earnings rank				
		[0,25]	[25,50]	[50,75]	[75,95]	[95,100]
Innovation by the firm, A_f	Low	-2.52	-2.34	-2.21	-2.08	-1.85
		[-18.31]	[-15.95]	[-13.94]	[-13.92]	[-9.43]
	High	-1.38	-1.45	-1.53	-1.51	-1.21
		[-9.15]	[-10.3]	[-10.9]	[-10.69]	[-7.09]
Innovation by competitors, $A_{I\setminus f}$	Low	-1.57	-0.65	-0.16	0.86	0.81
		[-6.12]	[-2.49]	[-0.59]	[3.09]	[2.35]
	High	-0.35	0.07	0.54	0.96	1.11
		[-1.19]	[0.24]	[1.99]	[3.48]	[3.73]
B. Number of years unemployed, 5yr horizon (conditional on having left firm within 3 yrs)						
Innovation	Tenure	Earnings rank				
		[0,25]	[25,50]	[50,75]	[75,95]	[95,100]
Innovation by the firm, A_f	Low	0.12	1.15	1.05	1.37	2.65
		[0.47]	[5.67]	[4.81]	[4.49]	[4.67]
	High	1.34	2.25	1.86	2.2	3.27
		[4.68]	[8.11]	[7.88]	[6.47]	[6.04]
Innovation by competitors, $A_{I\setminus f}$	Low	0.11	2.16	3.03	3.93	3.64
		[0.3]	[6.55]	[9.69]	[10.94]	[6.87]
	High	-1.33	0.38	2.97	3.99	4.08
		[-2.94]	[1.09]	[8.38]	[8.49]	[6.34]
C. Application for disability insurance (DI), 5yr horizon (conditional on having left firm within 3 yrs)						
Innovation	Tenure	Earnings rank				
		[0,25]	[25,50]	[50,75]	[75,95]	[95,100]
Innovation by the firm, A_f	Low	-0.1	0.08	0.07	0.06	0.08
		[-3.36]	[2.63]	[4.03]	[3.79]	[3.22]
	High	0.01	0.04	0.06	0.09	0.1
		[0.34]	[1.31]	[2.73]	[5.63]	[5.36]
Innovation by competitors, $A_{I\setminus f}$	Low	-0.33	-0.05	0.15	0.41	0.38
		[-4.93]	[-0.9]	[3.7]	[8.33]	[5.31]
	High	-0.45	-0.27	0.07	0.27	0.35
		[-4.84]	[-4.31]	[1.35]	[6.17]	[5.91]

Note: This table reports an extension of the results reported in Table 2 in the paper, in which we allow the effects to vary with earnings rank and worker tenure. Specifically, we separate workers into two groups based on whether Panel A reports OLS estimates of equation (15) in the paper, where the dependent variable is multiplied by 100. In Panel B, the dependent variable is 100 $\times$ a count of the number of years of zero W2 earnings worker i has experienced between years $t+1$ and $t+5$. Panel C reports estimates of equation (16) in the paper. The dependent variable is 100 $\times$ a dummy that takes the value of if worker i has applied for disability insurance at any point between years $t+1$ and $t+5$. In both cases, we allow the response of the dependent variable to innovation (by the firm A_f or its competitors $A_{I\setminus f}$) to vary based on the worker's earnings rank, which are defined net of deterministic life-cycle effects, and whether the worker's tenure within the firm was above or below the median value of 3 years. The coefficients are standardized to a unit-standard deviation shock in A_f (overall firm innovation) and coefficients on competitor innovation are omitted for brevity. Standard errors, in parentheses, are clustered at the firm level.