Online Appendix to

"Looking Backward, Innovating Forward: A Theory of Competitive Cascades"

by

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E. Online Appendix

E.1. Additional Results for Appendix B: Data Description

E.1.1. Firm Counts in the CME Data

Table B.1 compares firm counts by year in our CME sample with numbers reported by the Chinese National Bureau of Statistics and by Brandt et al. (2014).

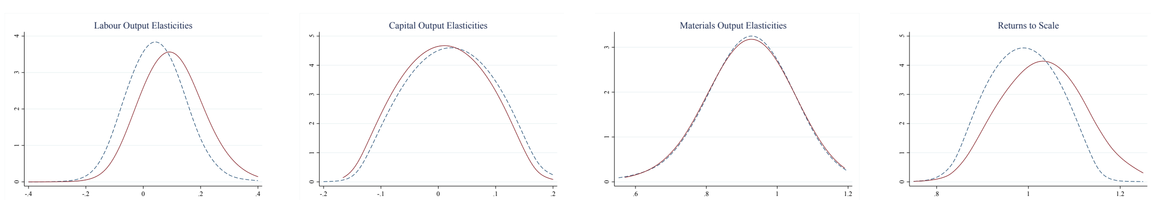
Table B.1: Number of Firms per Year

Author	2000	2001	2002	2003	2004	2005	2006
Official	162,885	171,256	181,557	196,222	276,474	271,835	301,961
Brandt et. al	162,883	169,030	181,557	196,222	279,092	271,835	301,961
Here	162,881	169,027	181,555	196,218	276,441	271,805	301,941

Notes: The first line is from the Chinese Statistical Yearbook as reported in Brandt et al. (2014, table 1). The second line is from Brandt et al. (2014, table 1). The third line is our data.

E.1.2. Details of Productivity Estimates

Figure B.1: Output Elasticities and Returns to Scale



Notes: This figure displays output elasticities for labour, capital and materials as well as returns to scale. The dashed-line distribution is the 'simple' case and the solid-line distribution is the 'complex' case that are described in the text and appendix B. Letting β_{ij} be the coefficient in the translog production function on the interaction between the log of inputs i and j, the panels report labour output elasticities ($\beta_L + 2\beta_{LL}l_{it} + \beta_{LK}k_{it}$), capital output elasticities ($\beta_K + 2\beta_{KK}k_{it} + \beta_{LK}l_{it}$), materials output elasticity ($\beta_M + 2\beta_{MM}m_{it} + \beta_{LM}m_{it} + \beta_{KM}k_{it}$), and returns to scale (the sum of the labour, capital and materials elasticities). Since output elasticities and returns to scale vary across firm-year observations, the distributions are based on 1,047,177 firm-year observations.

E.1.3. Principal Component of Innovation: Factor Loadings

The principal component of innovation is the principal component of the log of one plus R&D expenditures, the log of one plus new-product sales and the log of one plus patents. Table B.2 reports the factor loadings for each of our 28 industries. The loadings are always positive, meaning that higher levels of R&D, new-product sales, and patents

Table B.2: Factor Loadings for the Principal Component of Innovation

Industry	R&D	New-Product Sales	Patents	Industry	R&D	New-Product Sales	Patents
13	0.66	0.64	0.38	28	0.67	0.56	0.49
14	0.66	0.60	0.46	29	0.65	0.60	0.46
15	0.61	0.61	0.51	30	0.67	0.60	0.44
17	0.66	0.63	0.41	31	0.65	0.62	0.44
18	0.68	0.64	0.36	32	0.61	0.57	0.55
19	0.69	0.68	0.25	33	0.63	0.56	0.54
20	0.69	0.64	0.34	34	0.66	0.59	0.46
21	0.68	0.59	0.45	35	0.64	0.61	0.48
22	0.68	0.60	0.43	36	0.63	0.60	0.49
23	0.66	0.62	0.43	37	0.63	0.60	0.49
24	0.66	0.61	0.44	39	0.63	0.60	0.49
25	0.63	0.56	0.53	40	0.64	0.59	0.49
26	0.64	0.59	0.49	41	0.65	0.61	0.46
27	0.65	0.60	0.47	42	0.67	0.58	0.47
				minimum	0.61	0.56	0.25
				maximum	0.69	0.68	0.53
				average	0.66	0.62	0.42

Notes: This table shows the factor loadings on R&D, new-product sales and patents in constructing the principal component of innovation described in Section 3. This is done separately for each of the listed 2-digit industries.

all lead to a larger principal component. The patent loadings are smaller and more dispersed, which means that patents carry relatively less weight in the principal component and that its importance varies by industry.

E.1.4. Imputation of Firm-Level Quantities and Prices, 2004–2006

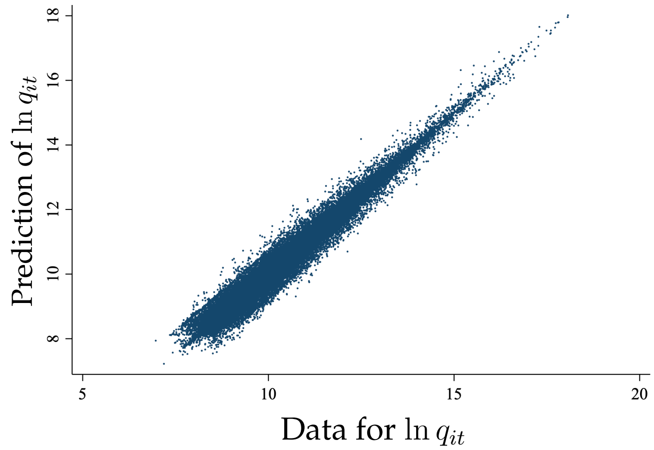
Quantity and price data are available for 2000–2003.[37] For 2004–2006, we impute q_{it} and then solve for prices using $p_{it} = r_{it}/q_{it}$ where r_{it} is revenues. To understand the imputation algorithm and appreciate its accuracy we first describe our algorithm using 2000–2001 quantity data to predict 2002–2003 quantity data. We then show that the correlation between the 2002–2003 prediction and the actual quantity data is 0.9899, meaning incredibly accurate. In step 1 we use 2000–2001 data to estimate the model:

$$\ln q_{it} = \beta_r \ln r_{it} + \beta_P P_{jt} + \beta_c \ln(c_{it}/r_{it}) + \alpha_{j_4} + \varepsilon_{it} \tag{E.1}$$

where i is firm, t is year, j is the firm's 2-digit industry, P_{jt} is the industry deflator from Brandt et al. (2017), c_{it} is cost of goods sold from the CME, and α_{j_4} is a 4-digit industry

[37] Brandt et al. (2017) use these data to build up the price indexes we used to construct TFPR.

Figure B.2: External Validation of Imputation Algorithm for Quantities, $t = 2002, 2003$



dummy. We have data on r_{it}, P_{jt} and c_{it}/r_{it} for every firm in every year. The idea behind equation (E.1) is that $\ln q_{it} = \ln r_{it} - \ln p_{it}$ by definition and we can proxy $\ln p_{it}$ with (1) the overall price index for the industry, which captures demand and supply shocks to all firms in the industry and is motivated by the approach in De Loecker (2011) and (2) the cost of goods sold, which captures firm-specific cost shocks. We have considered more variables such as firm-specific markups, but P_{jt} and $c \ln(c_{it}/r_{it})$ are enough to generate an almost perfect cross-validated out-of-sample prediction. In step 2, we consider a firm i born in year $t_{i0} > 2001$ i.e., born outside our 2000–2001 sample. Since we have estimates of the parameters of equation (E.1) and know r_{it}, P_{jt}, and $\ln(c_{it}/r_{it})$ beyond 2000–2001, we can use equation (E.1) to predict $\ln q_{it_{i0}}$ for $t_{i0} > 2001$. In step 3, we stack the data $\ln q_{it}$ ($t = 2000, 2001$) and $\ln q_{it_{i0}}$ ($t_{i0} = 2002, 2003$). We now have at least one observation for each firm in the 2000–2003 sample. Using the stacked data we estimate:

$$\ln q_{it} = \beta_r \ln r_{it} + \beta_P P_{jt} + \beta_c \ln(c_{it}/r_{it}) + \alpha_{j_4} + \alpha_i + \varepsilon_{it} \tag{E.2}$$

where this equation differs from (E.1) in that it has firm fixed effects α_i. (The point of step 2 is to allow us to estimate firm fixed effects for firms that were born after our 2000–2001 sample.) Having estimated equation (E.2), we use it to generate a prediction of $\ln q_{it}$ for $t = 2002, 2003$. The out-of-sample prediction is excellent. The correlation between the predicted and actual $\ln q_{it}$ in 2002–2003 is 0.9899 and the fit is illustrated in figure B.2. To impute q_{it} for 2004–2006, we repeat the above with 2000–2001 and 2002–2003 replaced by 2000–2003 and 2004–2006, respectively.

E.1.5. Measuring Quality with Customs Data

We merge the CME production data with HS8-level export and import data from the Chinese General Administration of Customs. Following Yu (2015), we match firms based on firm names, zip codes, and telephone numbers. We are able to match 76,946 firms, which is more than 40% of firms and more than 53% of total export value in the customs data.

Our starting point is Berry (1994) and its implementation by Khandelwal (2010). Consider a Chinese firm f in province p that exports an 8-digit HS good h to destination d in year t. A market or lower-tier nest is a triplet $m \equiv (h, d, t)$. Let H be a 2-digit HS code or upper -tier nest. Our demand equation is:

$$\ln q_{fhdt} = \beta^H \ln p_{fhdt} + \lambda_f^H + \lambda_{hdt}^H + \lambda_{pt}^H + \varepsilon_{fhdt}^H \tag{E.3}$$

where λ_f^H, λ_{hdt}^H and λ_{pt}^H are firm, market, and province-year fixed effects. We estimate this separately by h .We follow Khandelwal (2010) in winsorizing prices.[38] In Berry (1994), the dependent variable is divided by the size of the market and there is a random component of utility; however, both of these are collinear with the λ_{hdt}^H terms. A firm's quality in a market is $\lambda_{fhdt}^* \equiv \lambda_f^H + \lambda_{hdt}^H + \lambda_{pt}^H$ and we aggregate this up to the ft level as follows. First, we demean λ_{fhdt}^* by subtracting off the average quality in the market hdt because quality is not comparable across markets. Second, we take the weighted average of the demeaned λ_{fhdt}^* terms, weighted by the firm's exports to market hdt.

In equation (E.3), price is endogenous. We construct a novel instrument that avoids some of the criticisms of existing instruments (Ackerberg et al., 2007) by observing that while a firm may be a large employer in its industry within a city, the firm is typically a small employer in its city overall. Consider a firm in a 2-digit industry in a city and calculate the average wage paid by firms in that city who are *not* in that industry. This is a cost shifter that is exogenous to the firm and serves as our instrument.

To get a feel for the estimates, table B.3 reports estimates of equation (E.3) at the HS 'section' level for those sections that account for a total of 90% of all exports over 2000–6. Looking down the columns we see that the IV, first stage, and reduced form estimates are typically significant at the 1% level and that the IV estimate is more negative than the OLS estimate.

[38]We do so by first demeaning price within a market (h, d, t), then winsorizing prices above the 95th percentile and below the 5th percentile. Finally, we add the market mean back in.

Table B.3: Demand Estimation and Quality

Section	HS Section	IV		OLS		First Stage		X	Observations	Firms	*hdt* (#)	Weak
XVI	Machinery	-1.19*	(0.20)	-0.78*	(0.01)	0.51*	(0.07)	43%	2,941,071	16,058	145,464	51
XI	Textiles	-1.52*	(0.15)	-0.77*	(0.01)	0.35*	(0.04)	57%	3,017,017	14,971	103,255	90
XX	Misc. manufacturing	-0.78*	(0.21)	-0.72*	(0.01)	0.4*	(0.07)	64%	1,281,398	10,155	39,474	33
XV	Metal products	-1.89*	(0.48)	-1.06*	(0.02)	0.23*	(0.06)	70%	983,661	13,231	60,560	17
VI	Chemicals	-2.15*	(0.49)	-0.87*	(0.02)	0.18*	(0.05)	75%	744,847	6,625	63,694	14
XVII	Vehicles, planes, boats	-1.55*	(0.59)	-0.7*	(0.04)	0.37*	(0.10)	80%	346,292	3,442	18,692	13
VII	Plastics	-1.29*	(0.41)	-0.97*	(0.03)	0.34*	(0.07)	83%	912,161	14,160	35,027	27
XII	Footwear	-0.75*	(0.16)	-0.67*	(0.03)	0.67*	(0.11)	87%	519,547	4,833	12,818	35
XVIII	Optical, precision instr.	-0.75*	(0.28)	-0.69*	(0.01)	0.51*	(0.13)	90%	506,476	5,255	32,585	17

Notes: This table presents estimates of β^H in equation (E.3). The instrument for price is the average wage of other firms in the same city but not in the same 2-digit industry. 'First Stage' is the coefficient from a regression of price on the instrument (plus fixed effects). Standard errors are in parentheses and are clustered at the firm level. Rows are sorted by the size of exports. 'X' is the cumulative percentage of total exports over 2000–6 accounted for by the HS section, e.g., Machinery accounted for 43% of exports while Machinery plus Textiles accounted for 57%. 'Observations,' 'firms,' and (h, d, t) are the number of observations, firms, and markets, respectively. 'Weak' is the Kleibergen-Paap F-statistic for weak instruments. A * indicates statistical significance at the 1% level.

E.1.6. Details on Standard Error Clustering

We claimed in the main text that we are using conservative standard errors. We document this here. Consider table B.4. This reports estimates of our baseline specification for the principal component of innovation (table 2, column 7), which means a specification with our six key variables as well as lagged innovation $\omega_{i,t-1}$, the probability of exporting p_{ijt}, firm fixed effects, and gjt fixed effects where g is the lagged grade. The first row reports the estimated coefficients. Each subsequent pair of rows reports clustered and cluster-bootstrapped standard errors. A * next to a standard error means that, using that standard error, the coefficient in that column is statistically significant at the 1% level. The clustering variables are indicated to the left and, where variables are separated by commas, there is two-way clustering. In the main-text tables reporting our baseline specification, the clustering variables are firm and grade-industry (gj). For reference, these appear in boldface in table B.4.[39]

In the 'firm-year' rows we cluster at the observation level i.e., we use robust standard errors. These are smaller than the boldface standard errors. To deal with serial correlation, in the 'firm' row we cluster by firm. This makes little difference. In the 'firm, grade-industry-year' we cluster by firm and gjt, which grows the standard errors just a little.

[39]Bootstrapping is done using the Stata bootstrap command with gj resampling, meaning our samples are representative of the population sample of gj clusters. Note that we are *not* using the wild clustered bootstrap, which is unnecessary here given the large number of clusters. (While how to count clusters in our setting is not obvious, at a minimum a cluster is gj so that we have *at least* 8 × 28 = 224 clusters.)

Table B.4: Choice of Standard Errors

		Exports (r) Backward	Exports (r) Forward	Competition (n) Backward	Competition (n) Forward	Competition (ω) Backward	Competition (ω) Forward
		$p_{ijt}\bar{r}_{jt}^{g(i)-1}$	$p_{ijt}\bar{r}_{jt}^{g(i)+1}$	$p_{ijt}n_{jt}^{g(i)-1}$	$p_{ijt}n_{jt}^{g(i)+1}$	$p_{ijt}\bar{\omega}_{jt}^{g(i)-1}$	$p_{ijt}\bar{\omega}_{jt}^{g(i)+1}$
Clustering variables	Type	(1)	(2)	(3)	(4)	(5)	(6)
	Coefficient	-0.62	0.22	0.59	-0.29	0.13	0.06
firm-year (robust)	Cluster	0.06*	0.04*	0.06*	0.04*	0.02*	0.02*
	Bootstrap	0.06*	0.05*	0.06*	0.04*	0.02*	0.03
firm	Cluster	0.06*	0.05*	0.06*	0.05*	0.02*	0.02
	Bootstrap	0.06*	0.05*	0.06*	0.04*	0.03*	0.03
firm, grade-industry-year	Cluster	0.08*	0.05*	0.07*	0.05*	0.03*	0.03
	Bootstrap	0.08*	0.06*	0.09*	0.06*	0.02*	0.03
firm, grade-industry	Cluster	**0.08***	**0.06***	**0.07***	**0.06***	**0.04***	**0.03**
	Bootstrap	**0.11***	**0.06***	**0.11***	**0.07***	**0.04***	**0.04**
firm, industry-year	Cluster	0.08*	0.06*	0.08*	0.06*	0.03*	0.03
	Bootstrap	0.10*	0.07*	0.09*	0.07*	0.04*	0.05
firm, industry	Cluster	0.11*	0.07*	0.09*	0.08*	0.04*	0.04
	Bootstrap	0.12*	0.07*	0.10*	0.10*	0.04*	0.04

In the main text we expressed concern about correlations across neighbouring grades. To address this we drop the grade clustering and instead cluster by firm and industry-year jt. This leads to standard errors that are about the same or slightly smaller than our baseline standard errors (in boldface). Allowing for serial correlation using firm and industry clusters (last rows) generates slightly larger standard errors, but the increase is never more than 10% and has no influence on whether our coefficients are significant at the 1% level. Summarizing, two conclusions emerge. First, we are using conservative standard errors, ones which are at times twice as large as robust standard errors. Second, in every single case in the table, we have statistical significance at the 1% level regardless of how we cluster.

E.1.7. Comparison of Grade Data with Foster et al. (2008)

Our quality and grade assignments are, at bottom, firm-specific demand shifters and so can be compared to those in Foster et al. (2008). First, they find a high degree of persistence in firm-specific demand shifters. The annual persistence is 0.91 in their work and 0.92 in ours. Second, firm-specific demand shifters for exiters are 0.35 log points lower in their work and 0.38 lower in ours. Likewise, firm-specific demand shifters for entrants are 0.56 log points lower in their work and 0.41 lower in ours. Third, in a probit of exit on firm-specific demand shifters, the coefficient is -0.047 in their work and -0.062 in ours. In short, our grade dynamics are similar to the demand-shifter dynamics in Foster et al..

Table B.5: Baseline without p_{ijt} and ω_{it}

	Principal Component			R&D			New-Product Sales			Patents		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Exports (r) Backward	-0.88*	-0.60*	-0.59*	-0.35*	-0.22*	-0.21*	-0.21*	-0.17*	-0.16*	-0.026*	-0.011	-0.005
$p_{ijt}\bar{r}_{jt}^{g(i)-1}$ $(-)$	(0.08)	(0.08)	(0.09)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.006)	(0.005)	(0.005)
Exports (r) Forward	0.42*	0.23*	0.19*	0.13*	0.05	0.03	0.17*	0.16*	0.15*	0.018*	0.007	0.001
$p_{ijt}\bar{r}_{jt}^{g(i)+1}$ $(+)$	(0.06)	(0.06)	(0.07)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.005)	(0.004)	(0.004)
Competition (n) Backward	0.77*	0.59*	0.56*	0.26*	0.19*	0.19*	0.23*	0.21*	0.16*	0.019*	0.009	0.004
$p_{ijt}n_{jt}^{g(i)-1}$ $(+)$	(0.08)	(0.08)	(0.08)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.005)	(0.004)	(0.004)
Competition (n) Forward	-0.36*	-0.28*	-0.24*	-0.11*	-0.08*	-0.07*	-0.15*	-0.16*	-0.13*	-0.011*	-0.006	-0.000
$p_{ijt}n_{jt}^{g(i)+1}$ $(-)$	(0.06)	(0.06)	(0.06)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.004)	(0.003)	(0.003)
Competition (ω) Backward	0.24*	0.13*	0.12*	0.11*	0.06*	0.04*	0.05*	0.04*	0.04*	0.009*	0.005*	0.003
$p_{ijt}\bar{\omega}_{jt}^{g(i)-1}$ $(+)$	(0.04)	(0.04)	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.002)	(0.002)	(0.002)
Competition (ω) Forward	-0.08	0.06	0.05	-0.03	0.02	0.03	-0.02	0.00	-0.01	-0.008*	-0.002	-0.001
$p_{ijt}\bar{\omega}_{jt}^{g(i)+1}$ $(-)$	(0.04)	(0.03)	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.002)	(0.002)	(0.002)
Fixed effects #2	*jt*	*gjt*	*gjpt*	*jt*	*gjt*	*gjpt*	*jt*	*gjt*	*gjpt*	*jt*	*gjt*	*gjpt*
Fixed effects #3	*gj*			*gj*			*gj*			*gj*		
F tests												
$p\,\bar{r}^{g-1} = p\,\bar{r}^{g+1}$	105.58*	42.22*	32.00*	58.54*	32.37*	21.03*	57.47*	35.19*	38.24*	21.30*	5.52	0.65
$p\,n^{g-1} = p\,n^{g+1}$	105.54*	62.73*	50.92*	58.53*	45.64*	40.43*	49.59*	40.61*	32.29*	14.02*	5.19	0.53
$p\bar{\omega}^{g-1} = p\bar{\omega}^{g+1}$	17.02*	1.29	1.20	15.11*	1.82	0.22	9.67*	2.36	5.70	18.32*	4.21	2.32
All Six = 0	48.28*	40.22*	29.95*	20.33*	17.89*	18.87*	34.66*	31.36*	24.67*	5.98*	3.56*	3.62*
Observations	621,879	621,852	613,799	517,173	517,156	510,600	611,376	611,361	602,937	622,169	622,142	614,087
R^2	0.726	0.729	0.755	0.682	0.686	0.714	0.739	0.740	0.772	0.566	0.571	0.605
Mean of dep. var.	0.064	0.064	0.064	0.597	0.597	0.597	0.949	0.949	0.949	0.042	0.042	0.042

Notes: This table contains the same specifications as in tables 2 and 3 except that lagged productivity $\omega_{i,t-1}$ and the probability of exporting p_{ijt} are not included as regressors. **The table shows that excluding lagged productivity $\omega_{i,t-1}$ and the probability of exporting p_{ijt} has no impact on our baseline estimates.**

Table B.6: Full Set of Results for R&D

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exports (r) Backward	-0.29*	-0.30*	-0.26*	-0.28*	-0.33*	-0.35*	-0.21*	-0.21*
$p_{ijt}\bar{r}_{jt}^{g(i)-1}$ (−)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.03)	(0.03)
	[0.06]*	[0.06]*	[0.06]*	[0.06]*	[0.06]*	[0.06]*	[0.04]*	[0.04]*
Exports (r) Forward	0.10*	0.11*	0.09*	0.10*	0.13*	0.15*	0.05	0.04
$p_{ijt}\bar{r}_{jt}^{g(i)+1}$ (+)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)
	[0.03]*	[0.03]*	[0.02]*	[0.03]*	[0.03]*	[0.03]*	[0.02]	[0.03]
Competition (n) Backward	0.23*	0.24*	0.20*	0.21*	0.26*	0.27*	0.18*	0.18*
$p_{ijt}n_{jt}^{g(i)-1}$ (+)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)
	[0.05]*	[0.05]*	[0.05]*	[0.05]*	[0.05]*	[0.05]*	[0.03]*	[0.03]*
Competition (n) Forward	-0.12*	-0.12*	-0.09*	-0.09*	-0.11*	-0.11*	-0.07*	-0.07*
$p_{ijt}n_{jt}^{g(i)+1}$ (−)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
	[0.02]*	[0.02]*	[0.02]*	[0.02]*	[0.03]*	[0.03]*	[0.02]*	[0.02]*
Competition (ω) Backward	0.09*	0.10*	0.09*	0.10*	0.11*	0.11*	0.06*	0.04*
$p_{ijt}\bar{\omega}_{jt}^{g(i)-1}$ (+)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
	[0.02]*	[0.02]*	[0.02]*	[0.02]*	[0.02]*	[0.02]*	[0.02]*	[0.02]*
Competition (ω) Forward	-0.03	-0.03	-0.02	-0.03	-0.03	-0.04	0.02	0.03
$p_{ijt}\bar{\omega}_{jt}^{g(i)+1}$ (−)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.01]
Lagged productivity	-0.07*	-0.07*	-0.07*	-0.07*	-0.05*	-0.04*	-0.04*	-0.03*
$\omega_{i,t-1}$	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	[0.01]*	[0.01]*	[0.01]*	[0.01]*	[0.01]*	[0.01]*	[0.01]*	[0.01]*
Prob. of exporting	0.02	0.03	-0.00	0.00	-0.02	-0.02	-0.02	-0.01
p_{ijt}	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.01]
Fixed effects #2	*jt*	*jpt*	*jt*	*jpt*	*jt*	*jpt*	*gjt*	*gjpt*
Fixed effects #3			*g*	*g*	*gj*	*gjp*		
F tests								
$p\,\bar{r}^{g-1} = p\,\bar{r}^{g+1}$	51.03*	55.94*	40.05*	43.68*	52.19*	58.14*	29.72*	21.23*
$p\,n^{g-1} = p\,n^{g+1}$	53.55*	59.23*	37.14*	40.27*	46.30*	49.54*	38.23*	38.24*
$p\bar{\omega}^{g-1} = p\,\bar{\omega}^{g+1}$	16.03*	18.43*	14.32*	16.83*	14.47*	16.53*	1.49	0.18
All Six = 0	17.57*	18.38*	15.86*	16.42*	20.30*	21.62*	16.04*	16.12*
Observations	517,173	515,185	517,173	515,185	517,173	514,795	517,156	510,600
R^2	0.680	0.687	0.680	0.688	0.682	0.696	0.687	0.714

Notes: This table is the same as table 2 except that the dependent variable is now the log of one plus R&D. Note that these data are not available in 2000 and 2004. The mean of the dependent variable is 0.597. **This table shows that our baseline R&D results (column 7) are not perversely driven by the complex firm and grade-industry-year gjt fixed effects.**

Table B.7: Full Set of Results for New-Product Sales

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exports (r) Backward	-0.24*	-0.24*	-0.21*	-0.23*	-0.25*	-0.24*	-0.22*	-0.19*
$p_{ijt}\bar{r}_{jt}^{g(i)-1}$ (−)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
	[0.04]*	[0.04]*	[0.04]*	[0.04]*	[0.04]*	[0.03]*	[0.04]*	[0.03]*
Exports (r) Forward	0.15*	0.14*	0.15*	0.13*	0.16*	0.16*	0.15*	0.12*
$p_{ijt}\bar{r}_{jt}^{g(i)+1}$ (+)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)
	[0.03]*	[0.03]*	[0.03]*	[0.02]*	[0.03]*	[0.02]*	[0.04]*	[0.03]*
Competition (n) Backward	0.25*	0.23*	0.23*	0.21*	0.25*	0.20*	0.23*	0.18*
$p_{ijt}n_{jt}^{g(i)-1}$ (+)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)
	[0.04]*	[0.04]*	[0.05]*	[0.04]*	[0.04]*	[0.03]*	[0.05]*	[0.03]*
Competition (n) Forward	-0.19*	-0.15*	-0.16*	-0.14*	-0.17*	-0.13*	-0.18*	-0.14*
$p_{ijt}n_{jt}^{g(i)+1}$ (−)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
	[0.03]*	[0.02]*	[0.03]*	[0.02]*	[0.03]*	[0.02]*	[0.04]*	[0.03]*
Competition (ω) Backward	0.04*	0.05*	0.04*	0.05*	0.05*	0.07*	0.04*	0.04*
$p_{ijt}\bar{\omega}_{jt}^{g(i)-1}$ (+)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	[0.02]	[0.02]*	[0.02]	[0.02]*	[0.01]*	[0.01]*	[0.01]*	[0.01]*
Competition (ω) Forward	-0.02	-0.03*	-0.01	-0.03*	-0.02	-0.04*	-0.00	-0.01
$p_{ijt}\bar{\omega}_{jt}^{g(i)+1}$ (−)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]*	[0.02]	[0.01]
Lagged productivity	-0.08*	-0.06*	-0.08*	-0.06*	-0.05*	-0.04*	-0.05*	-0.04*
$\omega_{i,t-1}$	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	[0.02]*	[0.02]*	[0.01]*	[0.01]*	[0.01]*	[0.01]*	[0.01]*	[0.01]*
Prob. of exporting	0.09*	0.08*	0.06*	0.06*	0.06*	0.04*	0.07*	0.05*
p_{ijt}	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	[0.02]*	[0.02]*	[0.02]*	[0.02]*	[0.02]*	[0.02]	[0.02]*	[0.02]*
Fixed effects #2	*jt*	*jpt*	*jt*	*jpt*	*jt*	*jpt*	*gjt*	*gjpt*
Fixed effects #3			*g*	*g*	*gj*	*gjp*		
F tests								
$p\,\bar{r}^{g-1} = p\,\bar{r}^{g+1}$	72.02*	86.40*	61.14*	75.11*	71.28*	93.51*	46.75*	41.48*
$p\,n^{g-1} = p\,n^{g+1}$	81.65*	83.75*	64.63*	65.90*	62.21*	56.75*	52.36*	39.40*
$p\bar{\omega}^{g-1} = p\,\bar{\omega}^{g+1}$	5.94	17.96*	6.10	18.20*	10.66*	28.31*	3.44	6.05
All Six = 0	25.87*	25.09*	21.07*	20.37*	21.75*	22.28*	15.84*	12.28*
Observations	611,376	608,324	611,376	608,324	611,376	607,996	611,361	602,937
R^2	0.738	0.757	0.739	0.757	0.739	0.762	0.740	0.772

Notes: This table is the same as table 2 except that the dependent variable is now the log of one plus the value of new-product sales. Note that these data are not available in 2000 and 2004. The mean of the dependent variable is 0.949. **This table shows that our baseline new-product sales results (column 7) are not perversely driven by the complex firm and grade-industry-year gjt fixed effects.**

Table B.8: Full Set of Results for Patents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exports (r) Backward	-0.021*	-0.021*	-0.018*	-0.018*	-0.026*	-0.026*	-0.011	-0.005
$p_{ijt}\bar{r}_{jt}^{g(i)-1}$ $(-)$	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)
	[0.006]*	[0.006]*	[0.006]*	[0.006]*	[0.007]*	[0.007]*	[0.006]	[0.006]
Exports (r) Forward	0.012*	0.012*	0.013*	0.013*	0.018*	0.019*	0.007	0.001
$p_{ijt}\bar{r}_{jt}^{g(i)+1}$ $(+)$	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)
	[0.005]	[0.005]	[0.005]	[0.005]	[0.006]*	[0.007]*	[0.005]	[0.004]
Competition (n) Backward	0.015*	0.015*	0.012*	0.012*	0.019*	0.018*	0.009	0.004
$p_{ijt}n_{jt}^{g(i)-1}$ $(+)$	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)
	[0.005]*	[0.005]*	[0.005]	[0.005]	[0.006]*	[0.006]*	[0.005]	[0.005]
Competition (n) Forward	-0.010*	-0.010*	-0.008	-0.008	-0.011*	-0.010	-0.006	-0.000
$p_{ijt}n_{jt}^{g(i)+1}$ $(-)$	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
	[0.004]	[0.004]	[0.004]	[0.004]	[0.005]	[0.005]	[0.004]	[0.003]
Competition (ω) Backward	0.008*	0.008*	0.008*	0.008*	0.009*	0.010*	0.004	0.003
$p_{ijt}\bar{\omega}_{jt}^{g(i)-1}$ $(+)$	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
	[0.002]*	[0.002]*	[0.002]*	[0.002]*	[0.003]*	[0.003]*	[0.002]	[0.002]
Competition (ω) Forward	-0.007*	-0.008*	-0.007*	-0.007*	-0.008*	-0.008*	-0.002	-0.001
$p_{ijt}\bar{\omega}_{jt}^{g(i)+1}$ $(-)$	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
	[0.002]*	[0.002]*	[0.002]*	[0.002]*	[0.002]*	[0.003]*	[0.002]	[0.002]
Lagged productivity	-0.005*	-0.005*	-0.006*	-0.005*	-0.004*	-0.004*	-0.003*	-0.002
$\omega_{i,t-1}$	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
	[0.001]*	[0.001]*	[0.001]*	[0.001]*	[0.001]*	[0.001]*	[0.001]	[0.001]
Prob. of exporting	0.005	0.005	0.001	0.001	-0.001	-0.001	-0.000	-0.000
p_{ijt}	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.002]	[0.003]
Fixed effects #2	*jt*	*jpt*	*jt*	*jpt*	*jt*	*jpt*	*gjt*	*gjpt*
Fixed effects #3			*g*	*g*	*gj*	*gjp*		
F tests								
$p\,\bar{r}^{g-1} = p\,\bar{r}^{g+1}$	16.30*	16.13*	14.15*	14.02*	20.93*	20.16*	5.57	0.66
$p\,n^{g-1} = p\,n^{g+1}$	12.34*	12.44*	8.25*	8.09*	12.69*	11.18*	4.88	0.50
$p\bar{\omega}^{g-1} = p\,\bar{\omega}^{g+1}$	17.47*	17.46*	16.07*	16.15*	17.86*	18.78*	4.13	2.29
All Six = 0	5.40*	5.49*	4.65*	4.76*	5.88*	5.63*	3.06*	3.27*
Observations	622,169	620,305	622,169	620,305	622,169	619,994	622,142	614,087
R^2	0.565	0.572	0.565	0.572	0.566	0.581	0.571	0.605

Notes: This table is the same as table 2 except that the dependent variable is now the log of one plus patents. Note that these data are not available in 2000 and 2004. The mean of the dependent variable is 0.042. **This table shows that our baseline patent results (column 7) are not perversely driven by the complex firm and grade-industry-year gjt fixed effects.**

Table B.9: The Effect of Innovation on Grade and Quality: Additional Specifications

Panel A: Grade levels on period-t innovation

	Grade = $g(i,t)$				Quality = $\theta^{g(i,t)}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Principal Component, t	0.037*				0.036*			
	(0.002)				(0.002)			
R&D, t		0.026*				0.027*		
		(0.002)				(0.002)		
New-Product Sales, t			0.023*				0.023*	
			(0.001)				(0.001)	
Patents, t				0.079*				0.081*
				(0.008)				(0.007)
Observations	785,302	621,689	748,350	796,945	785,302	621,689	748,350	796,945
R^2	0.895	0.908	0.903	0.895	0.923	0.934	0.928	0.923

Panel B: Grade levels on period-(t-1) innovation

	Grade = $g(i,t)$				Quality = $\theta^{g(i,t)}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Principal Component, t-1	0.023*				0.021*			
	(0.002)				(0.001)			
R&D, t-1		0.014*				0.016*		
		(0.002)				(0.002)		
New-Product Sales, t-1			0.012*				0.012*	
			(0.001)				(0.001)	
Patents, t-1				0.052*				0.045*
				(0.009)				(0.008)
Observations	545,569	547,859	417,850	545,570	545,569	547,859	417,850	545,570
R^2	0.910	0.910	0.900	0.910	0.936	0.936	0.925	0.936

Panel C: Grade changes on period-t innovation

	Grade Change = $g(i,t)$ - $g(i,t$-1)				Quality Change = $\theta^{g(i,t)}$ - $\theta^{g(i,t-1)}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Principal Component, t-1	0.023*				0.014*			
	(0.002)				(0.002)			
R&D, t-1		0.014*				0.009*		
		(0.002)				(0.002)		
New-Product Sales, t-1			0.012*				0.008*	
			(0.001)				(0.002)	
Patents, t-1				0.052*				0.037*
				(0.009)				(0.012)
Observations	545,569	547,859	417,850	545,570	545,569	547,859	417,850	545,570
R^2	0.611	0.610	0.554	0.610	0.513	0.513	0.462	0.513

Notes: The following table complements appendix table A.1. In Panel A (B), each column is a regression of either grade or quality in period t on innovation in period t ($t-1$). In Panel C, each column is a regression of either grade change or quality change on a measure of innovation in period t. Each column is a regression, one column each for the principal component of innovation, log of one plus R&D, log of one plus new-product sales, or log of one plus patents. All specifications include firm and gjt fixed effects. In Panel A the sample size is large relative to the baseline because we are not using lagged exports required to construct p_{it}. In Panels B and C the sample size is small relative to the baseline because we are including lagged innovation, which can be missing. In column 2 of panels B and C we use interpolated 2004 R&D data when taking lags of 2005 R&D data. Standard errors clustered two-way by firm and gj are in parentheses. A * indicates significance at the 1% level. **This table illustrates that innovation leads to higher grades and quality as well as positive grade and quality changes and that this result does not depend on the lag structure of innovation or whether grade and quality are in levels or changes.**

Table B.10: Endogeneity of p_{ijt} and Alternative Mechanisms: R&D, New-Product Sales and Patents

	R&D					New-Product Sales					Patents				
		Add Sales,	Add Interactions:				Add Sales,	Add Interactions:				Add Sales,	Add Interactions:		
	Baseline	Employment	Productivity	Domestic Sales	Employment	Baseline	Employment	Productivity	Domestic Sales	Employment	Baseline	Employment	Productivity	Domestic Sales	Employment
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Interact with prob. of exporting															
Exports (r) Backward	-0.21*	-0.20*	-0.21*	-0.21*	-0.20*	-0.22*	-0.22*	-0.23*	-0.23*	-0.23*	-0.011	-0.011	-0.010	-0.010	-0.011
$p_{ijt}\bar{r}_{jt}^{g(i)-1}$ (−)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Exports (r) Forward	0.05	0.05	0.05	0.05	0.05	0.15*	0.15*	0.16*	0.16*	0.16*	0.007	0.007	0.006	0.006	0.005
$p_{ijt}\bar{r}_{jt}^{g(i)+1}$ (+)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Competition (n) Backward	0.18*	0.18*	0.18*	0.18*	0.18*	0.23*	0.23*	0.24*	0.24*	0.23*	0.009	0.009	0.008	0.008	0.009
$p_{ijt}n_{jt}^{g(i)-1}$ (+)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Competition (n) Forward	-0.07*	-0.07*	-0.07*	-0.07*	-0.07*	-0.18*	-0.17*	-0.19*	-0.18*	-0.19*	-0.006	-0.005	-0.005	-0.005	-0.005
$p_{ijt}n_{jt}^{g(i)+1}$ (−)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Competition (ω) Backward	0.06*	0.06*	0.06*	0.06*	0.06*	0.04*	0.04*	0.04*	0.04*	0.04*	0.004	0.004	0.004	0.004	0.004
$p_{ijt}\bar{\omega}_{jt}^{g(i)-1}$ (+)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Competition (ω) Forward	0.02	0.02	0.02	0.02	0.02	-0.00	-0.00	-0.00	-0.00	-0.00	-0.002	-0.002	-0.002	-0.002	-0.002
$p_{ijt}\bar{\omega}_{jt}^{g(i)+1}$ (−)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Additional Firm characteristics															
Lagged ln(Domestic Sales$_{i,t-1}$)		0.04*		0.05*			0.07*		0.07*			0.003*		0.004*	
		(0.01)		(0.01)			(0.01)		(0.01)			(0.001)		(0.001)	
Lagged ln(Employment$_{i,t-1}$)		0.10*			0.11*		0.10*			0.11*		0.007*			0.008*
		(0.01)			(0.01)		(0.02)			(0.02)		(0.001)			(0.001)
Interact with lagged productivity, domestic sales, or employment															
Exports (r) Backward			0.42	0.37	0.38			-0.18	-0.18	-0.17			-0.041	-0.046	-0.033
$z_{i,t-1}\bar{r}_{jt}^{g(i)-1}$ (+)			(0.23)	(0.22)	(0.23)			(0.32)	(0.32)	(0.32)			(0.041)	(0.042)	(0.037)
Exports (r) Forward			0.04	0.00	0.02			-0.75	-0.77	-0.74			0.024	0.023	0.022
$z_{i,t-1}\bar{r}_{jt}^{g(i)+1}$ (+)			(0.25)	(0.25)	(0.26)			(0.35)	(0.35)	(0.34)			(0.033)	(0.033)	(0.033)
Competition (n) Backward			-0.33	-0.23	-0.26			0.51	0.62	0.63			0.075	0.078	0.063
$z_{i,t-1}n_{jt}^{g(i)-1}$ (+)			(0.22)	(0.21)	(0.22)			(0.38)	(0.38)	(0.38)			(0.041)	(0.042)	(0.036)
Competition (n) Forward			0.18	0.25	0.22			1.13	1.21*	1.18*			0.033	0.034	0.034
$z_{i,t-1}n_{jt}^{g(i)+1}$ (−)			(0.36)	(0.36)	(0.37)			(0.44)	(0.44)	(0.44)			(0.050)	(0.050)	(0.050)
Competition (ω) Backward			-0.31	-0.31	-0.30			-0.05	-0.11	-0.15			-0.022	-0.019	-0.018
$z_{i,t-1}\bar{\omega}_{jt}^{g(i)-1}$ (+)			(0.21)	(0.21)	(0.22)			(0.21)	(0.21)	(0.22)			(0.025)	(0.025)	(0.024)
Competition (ω) Forward			-0.22	-0.22	-0.21			0.07	0.02	0.01			-0.049	-0.047	-0.048
$z_{i,t-1}\bar{\omega}_{jt}^{g(i)+1}$ (−)			(0.25)	(0.25)	(0.25)			(0.31)	(0.30)	(0.31)			(0.044)	(0.044)	(0.045)
F-test for 6 interactions with lagged prod, sales or employ			1.33	1.04	1.09			2.74	3.15*	2.88			1.54	1.58	1.41
Observations	517,156	514,767	517,156	517,156	514,767	611,361	608,559	611,361	611,361	608,559	622,142	619,585	622,142	622,142	619,585
R^2	0.687	0.688	0.687	0.687	0.688	0.740	0.740	0.740	0.740	0.740	0.571	0.571	0.571	0.571	0.571

Notes: This table is identical in structure to table 4 except that the dependent variables are now the log of one plus R&D, the log of one plus new-product sales or the log of one plus patents. All specifications include lagged productivity ($\omega_{i,t-1}$), the probability of exporting (p_{ijt}), firm fixed effects, and gjt fixed effects. In addition, column 3 includes the lagged log of domestic sales and column 4 includes the lagged log of employment. **In text table 4 we examined whether our key mechanism really worked through exporting or whether it appeared to do so because the probability of exporting is correlated with other observable firm characteristics such as lagged productivity, domestic sales, or employment. We concluded that there was no evidence of this. This was done for the principal component of innovation. In this table we draw the same conclusion for alternative measures of innovation. To see this note that for our six key variables, column 1 is the same as columns 2–5. Further, for the alternative interactions in columns 3–5, the coefficients are rarely significant. Evidently, the mechanism explaining our results is the one highlighted by our theory, namely, exporting.**

Table B.11: Leave-One-Province Out: Estimates for R&D, New-Product Sales, and Patents

	R&D					New-Product Sales					Patents				
		Leave one province out when constructing:					Leave one province out when constructing:					Leave one province out when constructing:			
		Lagged export status $\delta_{i,t-1}$		Every component of 6 key variables			Lagged export status $\delta_{i,t-1}$		Every component of 6 key variables			Lagged export status $\delta_{i,t-1}$		Every component of 6 key variables	
	Baseline	OLS	IV	OLS	IV	Baseline	OLS	IV	OLS	IV	Baseline	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Exports (r) Backward	-0.22*	-0.20*	-0.22	-0.20*	-0.23*	-0.17*	-0.19	-0.21	-0.08*	-0.08	-0.025*	-0.051*	-0.057*	-0.024*	-0.027*
$p_{ijt}\bar{r}_{jt}^{g(i)-1}$ $(-)$	(0.03)	(0.06)	(0.09)	(0.03)	(0.03)	(0.03)	(0.08)	(0.12)	(0.03)	(0.04)	(0.005)	(0.010)	(0.013)	(0.005)	(0.006)
Exports (r) Forward	0.05	0.05	0.04	0.04	0.04	0.16*	0.13*	0.14*	0.14*	0.16*	0.017*	0.030*	0.030*	0.014*	0.016*
$p_{ijt}\bar{r}_{jt}^{g(i)+1}$ $(+)$	(0.02)	(0.03)	(0.04)	(0.02)	(0.02)	(0.03)	(0.05)	(0.06)	(0.03)	(0.03)	(0.005)	(0.007)	(0.008)	(0.005)	(0.005)
Competition (n) Backward	0.19*	0.14	0.18	0.17*	0.20*	0.21*	0.19	0.27	0.07	0.07	0.018*	0.039*	0.048*	0.018*	0.021*
$p_{ijt}n_{jt}^{g(i)-1}$ $(+)$	(0.03)	(0.06)	(0.09)	(0.02)	(0.03)	(0.04)	(0.09)	(0.14)	(0.03)	(0.04)	(0.005)	(0.010)	(0.013)	(0.005)	(0.005)
Competition (n) Forward	-0.08*	-0.09	-0.08	-0.07*	-0.08*	-0.15*	-0.11*	-0.12	-0.12*	-0.15*	-0.010	-0.017	-0.017	-0.009	-0.009
$p_{ijt}n_{jt}^{g(i)+1}$ $(-)$	(0.02)	(0.04)	(0.05)	(0.02)	(0.02)	(0.03)	(0.04)	(0.06)	(0.03)	(0.03)	(0.004)	(0.007)	(0.008)	(0.004)	(0.004)
Competition (ω) Backward	0.06*	0.09*	0.10*	0.05*	0.06*	0.04*	0.06	0.04	0.05*	0.05*	0.009*	0.019*	0.016*	0.009*	0.009*
$p_{ijt}\bar{\omega}_{jt}^{g(i)-1}$ $(+)$	(0.01)	(0.03)	(0.04)	(0.01)	(0.02)	(0.01)	(0.03)	(0.04)	(0.01)	(0.01)	(0.002)	(0.005)	(0.005)	(0.002)	(0.002)
Competition (ω) Forward	0.02	0.03	0.05	0.02	0.02	0.00	-0.04	-0.04	-0.01	-0.01	-0.008*	-0.019*	-0.018*	-0.007*	-0.007*
$p_{ijt}\bar{\omega}_{jt}^{g(i)+1}$ $(-)$	(0.01)	(0.03)	(0.03)	(0.01)	(0.01)	(0.01)	(0.03)	(0.04)	(0.01)	(0.01)	(0.002)	(0.005)	(0.005)	(0.002)	(0.002)
Lagged productivity	-0.27*	-0.28*	-0.24*	-0.27*	-0.27*	-0.35*	-0.35*	-0.33*	-0.36*	-0.36*	-0.032*	-0.031*	-0.026*	-0.033*	-0.032*
$\omega_{i,t-1}$	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
	gjt	gjt	gjt	gjt	gjt	gjt	gjt	gjt	gjt	gjt	jt, gj	jt, gj	jt, gj	jt, gj	jt, gj
Observations	517,047	517,047	517,047	517,047	517,047	611,214	611,214	611,214	611,214	611,214	622,031	622,031	622,031	622,031	622,031
R^2	0.686	0.686		0.686		0.740	0.739		0.740		0.566	0.567		0.566	
Weak instrumnets F (KP)			194.20		1005.00			267.20		965.60			469.90		820.90

Notes: This table has the same format as columns 1–5 of table 5 except that the dependent variables are now the log of one plus R&D, the log of one new-product sales, and the log of one plus patents. All specifications include lagged productivity ($\omega_{i,t-1}$), the probability of exporting (p_{ijt}), firm fixed effects, and gjt fixed effects. For patents, the results are all insignificant with gjt fixed effects so we use gj and jt fixed effects. **In table 5 we were concerned about the endogeneity of our six key variables and used a leave-one-province-out strategy for showing that this concern was misplaced. In this table we repeat the excercise for our three disaggregated measures of innovation and show that the concern is misplaced for each of these. To see this, note that column 1 is similar to columns 2–5 (with some exceptions for new-product sales).**

Table B.12: Drop SOEs and FIEs: R&D, New-Product Sales and Patents

	R&D		New-Product Sales		Patents	
	Baseline	drop SOE+FIE	Baseline	drop SOE+FIE	Baseline	drop SOE+FIE
	(1)	(2)	(3)	(4)	(5)	(6)
Exports (r) Backward	-0.21*	-0.25*	-0.22*	-0.32*	-0.026*	-0.026*
$p_{ijt}\bar{r}_{jt}^{g(i)-1}$ $(-)$	(0.03)	(0.04)	(0.03)	(0.05)	(0.006)	(0.007)
Exports (r) Forward	0.05*	0.05	0.15*	0.23*	0.018*	0.021*
$p_{ijt}\bar{r}_{jt}^{g(i)+1}$ $(+)$	(0.02)	(0.03)	(0.03)	(0.05)	(0.005)	(0.005)
Competition (n) Backward	0.18*	0.20*	0.23*	0.34*	0.019*	0.015
$p_{ijt}n_{jt}^{g(i)-1}$ $(+)$	(0.03)	(0.04)	(0.04)	(0.06)	(0.005)	(0.006)
Competition (n) Forward	-0.07*	-0.09*	-0.18*	-0.27*	-0.011*	-0.012*
$p_{ijt}n_{jt}^{g(i)+1}$ $(-)$	(0.02)	(0.02)	(0.03)	(0.04)	(0.004)	(0.004)
Competition (ω) Backward	0.06*	0.07*	0.04*	0.06*	0.009*	0.012*
$p_{ijt}\bar{\omega}_{jt}^{g(i)-1}$ $(+)$	(0.01)	(0.02)	(0.01)	(0.02)	(0.002)	(0.002)
Competition (ω) Forward	0.02	0.02	-0.00	0.01	-0.008*	-0.010*
$p_{ijt}\bar{\omega}_{jt}^{g(i)+1}$ $(-)$	(0.01)	(0.01)	(0.01)	(0.02)	(0.002)	(0.002)
Lagged productivity	-0.04*	-0.04*	-0.05*	-0.05*	-0.004*	-0.002
$\omega_{i,t-1}$	(0.01)	(0.01)	(0.01)	(0.01)	(0.001)	(0.001)
Prob. of exporting	-0.02	-0.00	0.07*	0.04	-0.001	0.001
p_{ijt}	(0.01)	(0.02)	(0.01)	(0.02)	(0.002)	(0.003)
Fixed effects #2	gjt	gjt	gjt	gjt	gj and jt	gj and gj
F tests						
$p\,\bar{r}^{g-1} = p\,\bar{r}^{g+1}$	29.72*	26.75*	46.75*	44.23*	20.93*	20.98*
$p\,n^{g-1} = p\,n^{g+1}$	38.23*	29.00*	52.36*	52.06*	12.69*	9.14*
$p\bar{\omega}^{g-1} = p\,\bar{\omega}^{g+1}$	1.49	2.12	3.44	3.03	17.86*	27.19*
All Six = 0	16.04*	12.58*	15.84*	19.54*	5.88*	6.04*
Observations	517,156	374,556	611,361	431,385	622,169	438,694
R^2	0.687	0.691	0.740	0.727	0.566	0.568

Notes: The dependent variable appears in the header. 'Baseline' columns repeat the odd-numbered columns of table 3. All specifications include lagged productivity ($\omega_{i,t-1}$), the probability of exporting (p_{ijt}), firm fixed effects, and gjt fixed effects. For patents, half of the six key variables are insignificant with gjt fixed effects so we use gj and jt fixed effects. **This table shows that omitting SOEs and/or FIEs has little impact on our conclusions. If anything, omitting FIEs strengthens our results.**

Table B.13: Adding City Fixed Effects to Address Endogeneity

	R&D		New-Product Sales		Patents	
	Baseline	City FE	Baseline	City FE	Baseline	City FE
	(1)	(2)	(3)	(4)	(5)	(6)
Exports (r) Backward	-0.21*	-0.21*	-0.22*	-0.18*	-0.026*	-0.027*
$p_{ijt}\bar{r}_{jt}^{g(i)-1}$ $(-)$	(0.03)	(0.04)	(0.03)	(0.03)	(0.006)	(0.006)
Exports (r) Forward	0.05	0.04	0.15*	0.10*	0.018*	0.018*
$p_{ijt}\bar{r}_{jt}^{g(i)+1}$ $(+)$	(0.02)	(0.03)	(0.03)	(0.03)	(0.005)	(0.005)
Competition (n) Backward	0.18*	0.19*	0.23*	0.16*	0.019*	0.019*
$p_{ijt}n_{jt}^{g(i)-1}$ $(+)$	(0.03)	(0.03)	(0.04)	(0.03)	(0.005)	(0.005)
Competition (n) Forward	-0.07*	-0.07*	-0.18*	-0.12*	-0.011*	-0.010
$p_{ijt}n_{jt}^{g(i)+1}$ $(-)$	(0.02)	(0.02)	(0.03)	(0.03)	(0.004)	(0.004)
Competition (ω) Backward	0.06*	0.04	0.04*	0.03	0.009*	0.010*
$p_{ijt}\bar{\omega}_{jt}^{g(i)-1}$ $(+)$	(0.01)	(0.02)	(0.01)	(0.01)	(0.002)	(0.002)
Competition (ω) Forward	0.02	0.04	-0.00	-0.01	-0.008*	-0.008*
$p_{ijt}\bar{\omega}_{jt}^{g(i)+1}$ $(-)$	(0.01)	(0.01)	(0.01)	(0.01)	(0.002)	(0.002)
Lagged productivity	-0.04*	-0.03*	-0.05*	-0.03	-0.004*	-0.004*
$\omega_{i,t-1}$	(0.01)	(0.01)	(0.01)	(0.01)	(0.001)	(0.001)
Prob. of exporting	-0.02	-0.02	0.07*	0.06*	-0.001	-0.000
p_{ijt}	(0.01)	(0.01)	(0.01)	(0.01)	(0.002)	(0.003)
Fixed effects #2	*gjt*	*gjtc*	*gjt*	*gjtc*	*gj* and *jt*	*gjc* and *jtc*
F tests						
$p\,\bar{r}^{g-1} = p\,\bar{r}^{g+1}$	29.72*	16.59*	46.75*	25.70*	20.93*	19.39*
$p\,n^{g-1} = p\,n^{g+1}$	38.23*	31.42*	52.36*	27.09*	12.69*	10.64*
$p\bar{\omega}^{g-1} = p\,\bar{\omega}^{g+1}$	1.49	0.01	3.44	2.40	17.86*	18.00*
All Six = 0	16.04*	13.27*	15.84*	6.82*	5.88*	5.41*
Observations	517,156	464,119	611,361	507,269	622,169	619,008
R^2	0.687	0.729	0.740	0.797	0.566	0.594
Mean of dependent variable	0.597	0.597	0.949	0.949	0.042	0.042

Notes: The baseline columns repeat the results from columns 1, 3, and 5 of table 3. These specifications included lagged productivity ($\omega_{i,t-1}$), the probability of exporting (p_{ijt}), firm fixed effects, and grade-industry-year gjt fixed effects. In even-numbered columns we replace gjt fixed effects with grade-industry-year-*city* $gjtc$ fixed effects. For patents, all results are insignificant using gjt fixed effects so we use gj and jt fixed effects in column 5, gjc and jtc fixed effects in column 6. **Adding city fixed effects controls for regional agglomeration and other sources of cross-firm correlation in unobservables. Comparing odd and even columns, this control has very little effect on our baseline estimates, from which we conclude that such correlation across unobservables is not an important source of endogeneity bias.**

Table B.14: Repeat Table 2 Replacing the Principal Component of Innovation with its Lag

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exports (r) Backward	-0.95*	-0.94*	-0.89*	-0.89*	-1.07*	-1.08*	-0.70*	-0.65*
$p_{ijt}\bar{r}_{jt}^{g(i)-1}$ $(-)$	(0.10)	(0.10)	(0.10)	(0.10)	(0.11)	(0.11)	(0.10)	(0.10)
Exports (r) Forward	0.42*	0.38*	0.37*	0.33*	0.45*	0.46*	0.27*	0.22*
$p_{ijt}\bar{r}_{jt}^{g(i)+1}$ $(+)$	(0.07)	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)	(0.06)	(0.07)
Competition (n) Backward	0.87*	0.82*	0.79*	0.75*	0.95*	0.90*	0.65*	0.60*
$p_{ijt}n_{jt}^{g(i)-1}$ $(+)$	(0.10)	(0.09)	(0.10)	(0.10)	(0.11)	(0.10)	(0.10)	(0.09)
Competition (n) Forward	-0.55*	-0.48*	-0.46*	-0.39*	-0.48*	-0.42*	-0.42*	-0.34*
$p_{ijt}n_{jt}^{g(i)+1}$ $(-)$	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)	(0.06)	(0.06)
Competition (ω) Backward	0.23*	0.24*	0.25*	0.25*	0.28*	0.30*	0.19*	0.15*
$p_{ijt}\bar{\omega}_{jt}^{g(i)-1}$ $(+)$	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Competition (ω) Forward	-0.07	-0.10*	-0.06	-0.10*	-0.09	-0.13*	0.04	0.03
$p_{ijt}\bar{\omega}_{jt}^{g(i)+1}$ $(-)$	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)
Lagged productivity	-0.18*	-0.17*	-0.18*	-0.17*	-0.12*	-0.10*	-0.08*	-0.07*
$\omega_{i,t-1}$	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Prob. of exporting	0.34*	0.30*	0.27*	0.25*	0.23*	0.16*	0.22*	0.17*
p_{ijt}	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)
Fixed effects #2	*jt*	*jpt*	*jt*	*jpt*	*jt*	*jpt*	*gjt*	*gjpt*
Fixed effects #3			*g*	*g*	*gj*	*gjp*		
F tests								
$p\,\bar{r}^{g-1} = p\,\bar{r}^{g+1}$	93.63*	89.64*	76.38*	73.92*	96.76*	95.64*	45.86*	33.38*
$p\,n^{g-1} = p\,n^{g+1}$	113.12*	104.77*	86.22*	77.97*	95.41*	85.84*	62.41*	54.71*
$p\bar{\omega}^{g-1} = p\,\bar{\omega}^{g+1}$	18.57*	27.76*	18.81*	28.90*	20.24*	28.76*	4.90	3.40
All Six = 0	37.42*	32.71*	29.71*	26.01*	30.39*	25.84*	24.91*	20.15*
Observations	588,331	586,550	588,331	586,550	588,331	586,550	588,331	586,550
R^2	0.741	0.751	0.741	0.752	0.742	0.757	0.745	0.771
Mean of dep. var.	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.019

Notes: This table is identical to table 2 except that the dependent variable is $y_{ij,t-1}$ instead of y_{ijt} where y is the principal component of innovation. All specifications include firm fixed effects. Standard errors are two-way clustered by firm and gj. A * indicates statistical significance at the 1% level. **Coefficients are larger here than in table 2.**

Table B.15: Repeat Table 3 Replacing Dependent Variables with their Lags

	R&D		New-Product Sales		Patents	
	(1)	(2)	(3)	(4)	(5)	(6)
Exports (r) Backward	-0.21*	-0.21*	-0.33*	-0.24*	-0.018*	-0.008
$p_{ijt}\bar{r}_{jt}^{g(i)-1}$ $(-)$	(0.04)	(0.04)	(0.05)	(0.04)	(0.005)	(0.004)
Exports (r) Forward	0.06	0.08	0.15*	0.13*	0.013*	0.005
$p_{ijt}\bar{r}_{jt}^{g(i)+1}$ $(+)$	(0.03)	(0.04)	(0.04)	(0.04)	(0.004)	(0.004)
Competition (n) Backward	0.16*	0.18*	0.33*	0.23*	0.013*	0.006
$p_{ijt}n_{jt}^{g(i)-1}$ $(+)$	(0.04)	(0.04)	(0.06)	(0.04)	(0.005)	(0.004)
Competition (n) Forward	-0.09*	-0.11*	-0.19*	-0.17*	-0.010*	-0.007
$p_{ijt}n_{jt}^{g(i)+1}$ $(-)$	(0.02)	(0.03)	(0.04)	(0.04)	(0.003)	(0.003)
Competition (ω) Backward	0.07*	0.06*	0.09*	0.06*	0.008*	0.005*
$p_{ijt}\bar{\omega}_{jt}^{g(i)-1}$ $(+)$	(0.02)	(0.02)	(0.02)	(0.01)	(0.002)	(0.001)
Competition (ω) Forward	0.02	0.02	0.00	-0.01	-0.006*	-0.002
$p_{ijt}\bar{\omega}_{jt}^{g(i)+1}$ $(-)$	(0.02)	(0.02)	(0.02)	(0.02)	(0.002)	(0.001)
Lagged productivity	-0.02	-0.02	-0.05*	-0.05*	-0.005*	-0.003*
$\omega_{i,t-1}$	(0.01)	(0.01)	(0.01)	(0.01)	(0.001)	(0.001)
Prob. of exporting	0.01	0.01	0.19*	0.14*	0.001	0.002
p_{ijt}	(0.01)	(0.02)	(0.02)	(0.02)	(0.002)	(0.002)
Fixed effects #2	*gjt*	*gjpt*	*gjt*	*gjpt*	*jt*	*gjt*
Fixed effects #3					*gj*	
F tests						
$p\,\bar{r}^{g-1} = p\,\bar{r}^{g+1}$	21.23*	17.25*	45.72*	35.47*	15.49*	3.30
$p\,n^{g-1} = p\,n^{g+1}$	22.00*	25.07*	43.25*	37.46*	10.14*	3.94
$p\bar{\omega}^{g-1} = p\,\bar{\omega}^{g+1}$	2.90	1.21	6.32	5.68	16.22*	5.21
All Six = 0	11.73*	10.96*	26.81*	17.31*	5.83*	4.70*
Observations	417,249	415,658	529,409	526,664	592,788	592,788
R^2	0.617	0.654	0.739	0.771	0.568	0.572
Mean of dep. var.	0.530	0.530	0.870	0.870	0.037	0.037

Notes: This table is identical to table 3 except that the dependent variable is $y_{ij,t-1}$ instead of y_{ijt} where y is the log of one plus R&D (columns 1–2), the log of one plus new-product sales (columns 3–4), or the log of one plus patents (columns 5–6). All specifications include firm fixed effects. Standard errors are two-way clustered by firm and gj. A * indicates statistical significance at the 1% level. **Coefficients for R&D are about the same as in table 3. Coefficients for new-product sales are slightly larger here than in table 3. Coefficients for patents are slightly smaller here than in table 3.**

Table B.16: Choice of Number of Grades in k-Means Clustering

	R&D				New-Product Sales			
	G=6	G=8	G=10	G=12	G=6	G=8	G=10	G=12
Exports (r) Backward	-0.22*	-0.21*	-0.23*	-0.23*	-0.19*	-0.22*	-0.22*	-0.18*
$p_{ijt}\bar{r}_{jt}^{g(i)-1}$ $(-)$	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)
Exports (r) Forward	0.03	0.05	0.06*	0.07	0.12*	0.15*	0.14*	0.13*
$p_{ijt}\bar{r}_{jt}^{g(i)+1}$ $(+)$	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Competition (n) Backward	0.19*	0.18*	0.20*	0.19*	0.19*	0.23*	0.22*	0.17*
$p_{ijt}n_{jt}^{g(i)-1}$ $(+)$	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)
Competition (N) Forward	-0.07*	-0.07*	-0.08*	-0.08*	-0.15*	-0.18*	-0.14*	-0.09*
$p_{ijt}n_{jt}^{g(i)+1}$ $(-)$	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Competition (ω) Backward	0.05*	0.06*	0.07*	0.08*	0.03*	0.04*	0.06*	0.07*
$p_{ijt}\bar{\omega}_{jt}^{g(i)-1}$ $(+)$	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)
Competition (ω) Forward	0.03	0.02	0.01	0.00	0.00	-0.00	-0.03	-0.04
$p_{ijt}\bar{\omega}_{jt}^{g(i)+1}$ $(-)$	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)

	Patents				Principal Component of Innovation			
	G=6	G=8	G=10	G=12	G=6	G=8	G=10	G=12
Exports (r) Backward	-0.02*	-0.03*	-0.03*	-0.03*	-0.56*	-0.62*	-0.67*	-0.60*
$p_{ijt}\bar{r}_{jt}^{g(i)-1}$ $(-)$	(0.01)	(0.01)	(0.01)	(0.01)	(0.09)	(0.08)	(0.09)	(0.09)
Exports (r) Forward	0.01	0.02*	0.02*	0.01*	0.14	0.22*	0.23*	0.17
$p_{ijt}\bar{r}_{jt}^{g(i)+1}$ $(+)$	(0.00)	(0.00)	(0.00)	(0.00)	(0.06)	(0.06)	(0.06)	(0.07)
Competition (n) Backward	0.02*	0.02*	0.02*	0.02*	0.53*	0.59*	0.61*	0.54*
$p_{ijt}n_{jt}^{g(i)-1}$ $(+)$	(0.00)	(0.01)	(0.00)	(0.00)	(0.08)	(0.07)	(0.08)	(0.07)
Competition (N) Forward	-0.01	-0.01*	-0.01*	-0.01	-0.27*	-0.29*	-0.25*	-0.18*
$p_{ijt}n_{jt}^{g(i)+1}$ $(-)$	(0.00)	(0.00)	(0.00)	(0.00)	(0.05)	(0.06)	(0.06)	(0.06)
Competition (ω) Backward	0.01*	0.01*	0.01*	0.01*	0.12*	0.13*	0.17*	0.18*
$p_{ijt}\bar{\omega}_{jt}^{g(i)-1}$ $(+)$	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.04)	(0.04)	(0.04)
Competition (ω) Forward	-0.00*	-0.01*	-0.01*	-0.01*	0.07	0.06	0.01	0.00
$p_{ijt}\bar{\omega}_{jt}^{g(i)+1}$ $(-)$	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.03)	(0.03)	(0.04)

Notes: In this table we examine the choice of G. In our baseline we assigned firm-years to grades using k-means clustering with the number of clusters set at $G = 8$. Here we consider $G = 6, 8, 10, 12$. G and the dependent variable are indicated in the headers. Each column is a regression specified as in our baseline (column 7 of table 2) i.e., with firm and gjt fixed effects. The exception is for patents where we use firm, gj, and jt fixed effects because results are never significant with gjt fixed effects. Standard errors are two-way clustered by firm and gj. A * indicates significance at the 1% level. **Comparing results in column $G = 8$ with other columns, the results are largely insensitive to the choice of G.**

Table B.17: Backward and Forward Beyond One Grade

	Principal Component							R&D						
	k=1	*k*=2	*k*=3	*k*=4	*k*=5	*k*=6	*k*=7	*k*=1	*k*=2	*k*=3	*k*=4	*k*=5	*k*=6	*k*=7
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Exports (r) Backward	-0.62*	-0.35*	-0.24*	-0.19*	-0.15*	-0.11*	-0.11*	-0.21*	-0.12*	-0.08*	-0.07*	-0.06*	-0.05*	-0.05*
$\Sigma_{k'=1}^{k} p_{ijt}\, \bar{r}_{jt}^{g(i)-k'}$ $(-)$	(0.08)	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Exports (r) Forward	0.22*	0.12*	0.04	0.02	0.03	0.04*	0.04	0.05	0.02	0.00	-0.00	0.00	0.01	0.00
$\Sigma_{k'=1}^{k} p_{ijt}\, \bar{r}_{jt}^{g(i)+k'}$ $(+)$	(0.06)	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Competition (n) Backward	0.59*	0.33*	0.22*	0.18*	0.14*	0.12*	0.12*	0.18*	0.10*	0.07*	0.06*	0.05*	0.04*	0.04*
$\Sigma_{k'=1}^{k} p_{ijt}\, n_{jt}^{g(i)-k'}$ $(+)$	(0.07)	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Competition (n) Forward	-0.29*	-0.18*	-0.09*	-0.05*	-0.04*	-0.04*	-0.04*	-0.07*	-0.04*	-0.02*	-0.01	-0.01	-0.01	-0.01
$\Sigma_{k'=1}^{k} p_{ijt}\, n_{jt}^{g(i)+k'}$ $(-)$	(0.06)	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Competition (ω) Backward	0.13*	0.08*	0.06*	0.05*	0.04*	0.04*	0.04*	0.06*	0.03*	0.02*	0.02*	0.02*	0.02*	0.02*
$\Sigma_{k'=1}^{k} p_{ijt}\, \bar{\omega}_{jt}^{g(i)-k'}$ $(+)$	(0.04)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Competition (ω) Forward	0.06	0.03	0.03*	0.02*	0.02*	0.02*	0.02*	0.02	0.01	0.01*	0.01*	0.01*	0.01*	0.01*
$\Sigma_{k'=1}^{k} p_{ijt}\, \bar{\omega}_{jt}^{g(i)+k'}$ $(-)$	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

	New-Product Sales							Patents						
	k=1	*k*=2	*k*=3	*k*=4	*k*=5	*k*=6	*k*=7	*k*=1	*k*=2	*k*=3	*k*=4	*k*=5	*k*=6	*k*=7
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Exports (r) Backward	-0.22*	-0.12*	-0.07*	-0.05*	-0.04*	-0.03*	-0.03	-0.026*	-0.014*	-0.011*	-0.009*	-0.007*	-0.005*	-0.005*
$\Sigma_{k'=1}^{k} p_{ijt}\, \bar{r}_{jt}^{g(i)-k'}$ $(-)$	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.006)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Exports (r) Forward	0.15*	0.08*	0.05*	0.03*	0.03*	0.03*	0.03*	0.018*	0.008*	0.004*	0.002	0.002	0.002*	0.002
$\Sigma_{k'=1}^{k} p_{ijt}\, \bar{r}_{jt}^{g(i)+k'}$ $(+)$	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.005)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Competition (n) Backward	0.23*	0.11*	0.07*	0.05*	0.04*	0.04*	0.04*	0.019*	0.011*	0.008*	0.007*	0.006*	0.005*	0.005*
$\Sigma_{k'=1}^{k} p_{ijt}\, n_{jt}^{g(i)-k'}$ $(+)$	(0.04)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.005)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Competition (n) Forward	-0.18*	-0.10*	-0.06*	-0.04*	-0.04*	-0.04*	-0.04*	-0.011*	-0.006*	-0.003*	-0.002	-0.001	-0.001	-0.001
$\Sigma_{k'=1}^{k} p_{ijt}\, n_{jt}^{g(i)+k'}$ $(-)$	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.004)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Competition (ω) Backward	0.04*	0.03*	0.02*	0.02*	0.01*	0.01*	0.01*	0.009*	0.005*	0.003*	0.002*	0.002*	0.002*	0.002*
$\Sigma_{k'=1}^{k} p_{ijt}\, \bar{\omega}_{jt}^{g(i)-k'}$ $(+)$	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Competition (ω) Forward	-0.00	-0.00	-0.00	0.00	0.00	0.00	0.00	-0.008*	-0.003*	-0.002*	-0.001*	-0.001	-0.001	-0.001
$\Sigma_{k'=1}^{k} p_{ijt}\, \bar{\omega}_{jt}^{g(i)+k'}$ $(-)$	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)

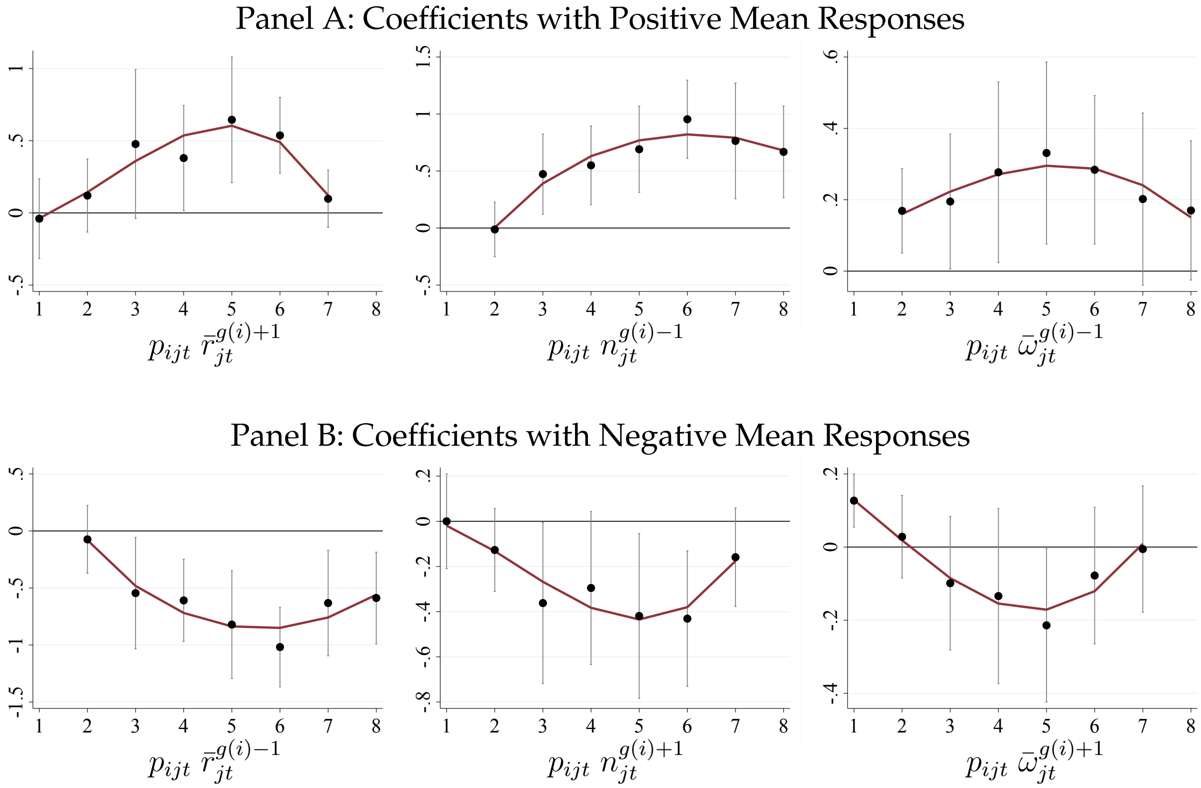
Notes: The dependent variable is identified in the panel headers. Column 1s are our baseline specifications (either column 7 of table 2 or the multiple column 1s of table 3). All specifications include lagged productivity, the probability of exporting p_{ijt}, and firm and gjt fixed effects. (For patents, this specification produces many zeros so we use gj and jt fixed effects.) Standard errors are two-way clustered by firm and grade-industry (gj). * indicates significance at the 1% level. **The remaining columns replace each of the six key variables with sums of the form $\sum_{k'=1}^{k} p_{ijt}\bar{r}_{jt}^{g(i)+k'}$ where k is listed in the column header. The theory states that coefficients shrink to 0 as k increases. This is precisely what the table shows.**

Table B.18: Inclusion of Grade $g(i)$

	Principal Component		R&D		New-Product Sales		Patents	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exports (r) Backward	-0.62*	-0.48*	-0.21*	-0.16*	-0.22*	-0.22*	-0.026*	-0.023*
$p_{ijt}\bar{r}_{jt}^{g(i)-1}$ (−)	(0.08)	(0.10)	(0.03)	(0.04)	(0.03)	(0.04)	(0.006)	(0.007)
Exports (r) Own Grade		0.13		0.06		0.11		0.013
$p_{ijt}\bar{r}_{jt}^{g(i)}$ (−)		(0.17)		(0.06)		(0.06)		(0.015)
Exports (r) Forward	0.22*	0.32*	0.05	0.08*	0.15*	0.14*	0.018*	0.021*
$p_{ijt}\bar{r}_{jt}^{g(i)+1}$ (+)	(0.06)	(0.07)	(0.02)	(0.02)	(0.03)	(0.04)	(0.005)	(0.006)
Competition (n) Backward	0.59*	0.54*	0.18*	0.16*	0.23*	0.22*	0.019*	0.019*
$p_{ijt}n_{jt}^{g(i)-1}$ (+)	(0.07)	(0.09)	(0.03)	(0.03)	(0.04)	(0.05)	(0.005)	(0.006)
Competition (n) Own Grade		-0.10		-0.06		-0.04		-0.012
$p_{ijt}n_{jt}^{g(i)}$ (+)		(0.12)		(0.05)		(0.05)		(0.010)
Competition (n) Forward	-0.29*	-0.24*	-0.07*	-0.05	-0.18*	-0.16*	-0.011*	-0.006
$p_{ijt}n_{jt}^{g(i)+1}$ (−)	(0.06)	(0.06)	(0.02)	(0.02)	(0.03)	(0.03)	(0.004)	(0.005)
Competition (ω) Backward	0.13*	0.04	0.06*	0.02	0.04*	0.04*	0.009*	0.006*
$p_{ijt}\bar{\omega}_{jt}^{g(i)-1}$ (+)	(0.04)	(0.04)	(0.01)	(0.02)	(0.01)	(0.01)	(0.002)	(0.002)
Competition (ω) Own Grade		0.26*		0.10*		0.00		0.012
$p_{ijt}\bar{\omega}_{jt}^{g(i)}$ (+)		(0.07)		(0.03)		(0.03)		(0.005)
Competition (ω) Forward	0.06	-0.09	0.02	-0.03	-0.00	-0.00	-0.008*	-0.015*
$p_{ijt}\bar{\omega}_{jt}^{g(i)+1}$ (−)	(0.03)	(0.06)	(0.01)	(0.02)	(0.01)	(0.02)	(0.002)	(0.004)
Lagged productivity	-0.11*	-0.11*	-0.04*	-0.03*	-0.05*	-0.05*	-0.004*	-0.004*
$\omega_{i,t-1}$	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.001)	(0.001)
Prob. of exporting	0.03	-0.25*	-0.02	-0.13*	0.07*	-0.01	-0.001	-0.014
$p_{ijt}^{g(i)}$	(0.03)	(0.09)	(0.01)	(0.03)	(0.01)	(0.04)	(0.002)	(0.007)
Fixed effects #2	*gjt*	*gjt*	*gjt*	*gjt*	*gjt*	*gjt*	*jt* and *gj*	*jt* and *gj*
Observations	621,852	621,852	517,156	517,156	611,361	611,361	622,169	622,169
R^2	0.729	0.729	0.687	0.687	0.74	0.74	0.566	0.566

Notes: The dependent variable is identified in the panel headers. Odd-numbered columns are our baseline specifications (either column 7 of table 2 or the multiple column 1s of table 3). All specifications include lagged productivity, the probability of exporting p_{ijt}, firm fixed effects and grade-industry-year fixed effects (gjt). (For patents, this specification produces many zeros so we use gj and jt fixed effects.) Standard errors are two-way clustered by firm and grade-industry (gj). * indicates significance at the 1% level. **Even-numbered columns add own-grade variables. Proposition 3 together with our empirical finding that the obsolescence rate η is close to 1/2 together imply that the own-grade coefficients should be zero. They are for $p_{ijt}\bar{r}_{jt}^{g(i)}$ and $p_{ijt}n_{jt}^{g(i)}$, but not for $p_{ijt}\bar{\omega}_{jt}^{g(i)}$.**

Figure B.3: Heterogeneous Responses



Notes: We re-estimate our principal component of innovation baseline specification (column 7 of table 2), but allowing our six key variables to vary by grade. The figure plots our estimated coefficients (dots) together with the corresponding 95% confidence intervals (vertical lines). (This is the only place in the paper where we do not use 1% significance because almost none of our many coefficients is significant at the 1% level.) Panel A shows results for the three variables that we expect to have positive coefficients (forward market size, backward extensive and intensive competition). Panel B shows results for the three variables that we expect to have negative coefficients (backward market size, forward extensive and intensive competition). **In almost all cases, our point estimates are of the expected sign despite the extensive heterogeneity now being allowed for, exactly as predicted by theory.**