Online Appendices for

"From 'Made in China' to 'Innovated in China': Necessity, Prospect, and Challenges'

Shang-Jin Wei, Zhuan Xie, and Xiaobo Zhang

Journal of Economic Perspectives, (31)1, Winter 2017

Online Appendix A: Decomposition of GDP Growth

To decompose GDP growth and to compute total factor productivity, we need data on physical capital, human capital, and output.

For physical capital, we refer to Li (2011) for a summary and comparison of different estimates in the existing literature. We use the investment data for 1953-2009 from Li (2011) and extend it to 2015 by using data on fixed capital formation from the National Bureau of Statistics, and employ a perpetual inventory method to estimate capital stock. For the discount rate, we use the data from Li (2011) before 1992, and 6% after 1992.[1] For price index, we use the "price index of fixed asset investment" provided by the National Bureau of Statistics, which is also Li's source for data before 1991.

Human capital is the product of the size of the labor force and average years of schooling. The size of labor force is from the National Bureau of Statistics. For average years of schooling, we use the estimates for 1978-2012 from Feng (2014) and extend it to 2015.

We need information on the share of labor income in national income. The share is computed by Li (2011) as 47% between 1993 and 2009. Based on data from National Bureau of Statistics, we compute the share to be about 50% between 2000 and 2015. We assume the share to be 50% in our baseline calculations.

Denoting the growth rates of physical capital, human capital and output by g_K, g_H and g_Y, respectively, the growth of total factor productivity is computed as:

TFP=g_Y -0.5*g_K -0.5*g_Y .

Out of concern that the estimated labor share in national income may be biased downward, we also use a share of 55%, 60% and 65% as sensitivity checks. We find that the new shares have only negligible effects on the TFP growth patterns.

We can do straightforward decomposition of GDP growth into contributions from various factors. The contributions from physical and human capital are 0.5*g_K/g_Y, and 0.5*g_H/g_Y, respectively, and that from TFP growth is 1 minus the contributions from the other two. The decomposition results are presented in Figure 1.

[1] As sensitivity checks, we have also used 5%, 8% and 10% as the discount rate. This makes some difference on the level of TFP but not much on the growth rate, which is the key interest of the paper.

Online Appendix B: Investigating the Underlying Causes of Innovation with Patent Data

Because many firms do not have patents and patent count does not follow a log-normal distribution, we cannot use ordinary least square regressions by taking the log on patent count. A common approach is to use a negative binomial model. However, all the observations with zero patents will be dropped when including firm fixed effects. Here we use a hybrid binomial estimation method proposed by Allison (2005): First, we compute the mean values of all the explanatory variables X. Second, we create a set of new variables by deducting the mean values from the original values of X—that is, X – mean of X. Third, we run a random negative binomial model on patent count using these newly created variables as independent variables. This method is a hybrid of the fixed effect and random effect models, largely overcoming the shortcomings of the conditional estimated fixed effect negative binomial model, which automatically drops observations with zero values for the outcome variable for all the years. The equation can be written as:

$P_{ijt} = F(Sales_{it}, Wage_{jt}, Subsidy_{jt}, Taxrate_{jt}, Interest\ rate_{jt}\ , Tariff_{jt}, Export_{it}, HH_{jt},$ industry or firm fixed effects, and year fixed effects),

where *P* = the number of approved patents for firm *i* in year *t, Sales* = firm *i*'s annual sales in year *t, Wage* = average wage at the city-industry-year-firm ownership level (excluding the firm itself) in the cell where the firm is located, *Subsidy* = the ratio of subsidies received from the government to total sales at the firm level*, Tax rate* = the sum of the income tax payment and value added tax payment relative to total sales at the firm level in year *t*, *Interest rate* = the ratio of total interest paid to the average liability this year and last year at the firm level*, Tariff* = weighted average of trade partners' tariff rates, based on matching product-level tariff data from the COMTRADE database with firm *i*'s SIC-2 code (computed at the industry-year level, which we use mainly to improve the matching rate); *Export* is a dummy variable indicating whether a firm has positive exports in year *t,* and finally *HH* is the Herfindahl-Hirschman (HH) index at the industry-year level. The HH index is calculated via the following steps: (1) for every four-digit industry and year *t*, compute every firm's market share, (2) for every four-digit industry and year *t*, sum the square of every firm's market share. The higher the HH index, the lower the degree of competition.

Many of the regressors are undoubtedly endogenous. In the spirit of an instrumental variable approach, we replace the wage rate, subsidy rate, tax rate, and interest rate from firm-year specific values with the average values of all other firms in the same cell of city-industry-ownership type-year. The idea (or the maintained assumption) is that the average values of all other firms in the same cell more likely reflect local labor market conditions (in the case of wage) or local policy designs (in the case of the other three variables). To do this exercise, we also drop all cells with fewer than five observations. Note that we regard the tariff variable as exogenous since it is the average of trading partners' tariff rates, which are unlikely to be systematically manipulated by individual firms in China.

Table A7 reports the hybrid negative binomial regression estimates. Several findings are apparent. First, firm size, measured by sales, is positively associated with the number of approved patents. Unsurprisingly, larger firms tend to have more patents approved. Second, export firms are more innovative. We refrain from assigning a causal interpretation to these two coefficients – the positive correlations between firm size and innovativeness and between export status and innovativeness could reflect causal effects in either direction (and probably in both directions). We simply treat these regressors as control variables.

Third, lower import tariff is good for firm innovations through the expansion of international markets for Chinese products. Because foreign tariffs are (largely) exogenous, we interpret this coefficient as reflecting a causal effect – expansion of international markets or export opportunities induces firms to do more innovations.

Fourth, in terms of the effects of fiscal subsidies, there is some evidence that invention patents respond positively to subsidies, but utility and design patents do not show statistically significant responses. Since invention patents are often regarded as "more innovative," one cannot rule out the possibility that firms' innovative activities respond to fiscal incentives.

Similarly, a higher tax rate appears to discourage innovation – the coefficients on the tax rate are negative in all four columns, though they are statistically significant for all patents, and invention and utility patents only.

Fifth, a higher cost of capital as measured by a higher implied interest rate also appears to discourage many types of innovative activities – the coefficients on log interest rate are negative and statistically significant for all patents, and utility and design patents.

Finally, there is a robust positive relationship between wage level and firm innovations. If our strategy of using the average wages of all other firms in the same cell to replace an individual firm's own wage succeeds in removing endogeneity, one might interpret the coefficient as saying that firms, on average, rise to the challenge of higher labor costs by engaging in more innovations.

Of course, innovative industries tend to hire more skilled workers than less innovative industries. In general, skilled workers earn more than unskilled workers, and thereby could produce a positive correlation between average wage and firm innovativeness at the industry level. Note that our regressions in Table A7 include separate firm and year fixed effects (and therefore subsuming separate industry fixed effects). So endogeneity has to come at the level of industry-city-ownership-year. Nonetheless, to further remove endogeneity, we replace current average wage by those of others firms in the same cell by its lagged value, and find qualitatively the same results. (The results are in Appendix Table A8.)

As robustness checks, we have implemented other specifications as well, such as fixed effect negative binomial model, random effect negative binomial model, and fixed effect ordinal linear probability model. The coefficients for most variables are qualitatively similar. We use minimum wage at the city-year level to replace the average wage of other firms in the same cell, and again find the same qualitative results (see Appendix Table A9).

The same wage increase means a different magnitude of cost shock to firms in labor-intensive industries and firms in other industries. To explore this feature, we now add an interaction term between the average wage of other firms in the same cell and a dummy indicating that the industry in which the firm operates has a labor intensity (labor cost as a share of total cost) above the median at the beginning of the sample. Appendix Table A10 displays the estimation results. The coefficient for the interaction term is positive and statistically significant among three out of four regressions (for total patents, and invention and design patents). Consistent with the induced innovation theory, rising labor costs have induced labor-intensive firms to become more innovative to survive. The results in Table A10 are again robust to the use of alternative wage variables (either lagged wages or legal minimum wages). To save space, the estimates using lagged wages or minimum wages are not reported here.

Studies like Autor et al. (2003) have shown that computer technology has reduced the demand for jobs involving routine tasks. Following Autor et al. (2003), we create a dummy variable "routine" indicating whether an industry involves more routine tasks (1) or not (0). Facing rising labor cost, we expect to see firms heavily involved in routine tasks, which are often done by low-skilled workers, to innovate more to substitute labor. Similar to Table A7, we use a differences-in-difference approach to examine the impact of rising wages on routine task-intensive industries by including an interaction term between wages and a "routine" dummy. As shown in Panel A of Table A11, the coefficient for the interaction term is statistically significant in all four regressions. In response to rising wages, in industries involving routine tasks, those firms that survive (i.e., continue to produce) tend to become more innovative, possibly by taking advantage of computer technologies.

When facing rising labor costs, there are two possible routes for labor-intensive industries. In industries where innovation is possible, firms have to innovate to survive. In industries in which international experience suggests that innovation is difficult (sunset industries), exit or closure is the likely outcome. In the sunset industries, with the dwindling market share, firms may be reluctant to make R&D investment for fear of failure to recoup the cost.

We define the sunset industries as follows: First, we select top 40 economies according to GDP in 2000 excluding China. Next we further narrow down the list by keeping countries with GDP per capita 1.5 times larger than that of China and lower than 12,000 USD (constant in 2005). The list ends up with Argentina, Brazil, Czech Republic, Mexico, Yemen, Poland, Russia, Turkey, Venezuela, and Zambia. Third, we calculate the annual growth rate of each industry by country and obtain the aggregate growth rate for all countries in the list using GDP as weights. An industry is defined as a sunset industry if its average growth rate during the period 1998–2007 is below the median growth rate among all the industries.

Panel B of Table A11 shows the estimates for the interaction term between wages and "sunset" industry dummy. The coefficient is only statistically negative in the regression on invention patents. Invention patents normally involve more R&D input than utility model and design patents. The results are robust when using lagged values of minimum wages in the interaction term. When market prospects loom large, the surviving firms in the sunset industries are less likely to make large R&D investment, thereby yielding a lower number of invention patents than in other industries. Like other economies which are slightly richer than China, the firms in the sunset industries in China will likely experience slower growth and are eventually replaced by sunrise industries.

Appendix Table A1—Number of Chinese Firms

Year	Firm count at year end	Private (%)	SOE (%)	Foreign (%)
1995	4,598,604	71	24	5
1996	4,997,932	72	23	5
1997	5,293,125	72	22	5
1998	5,526,172	73	21	5
1999	5,712,997	74	21	5
2000	5,875,706	76	19	5
2001	6,032,059	77	18	5
2002	6,356,801	79	16	5
2003	6,831,363	81	14	5
2004	7,400,172	83	12	5
2005	7,980,991	85	10	5
2006	8,572,472	86	9	5
2007	8,962,246	87	8	5
2008	9,405,281	88	7	5
2009	10,130,705	89	6	5
2010	11,150,201	90	5	5
2011	12,352,627	91	5	4
2012	13,433,213	92	4	4
2013	15,184,602	93	3	4
2014	18,178,921	94	3	3
Annual growth rate in different periods (%)				
1995–2005	6	8	-3	5
2005–2014	10	11	-5	3
1995–2014	8	9	-4	4

Note: Tabulated by authors based on China Firm Registry Database. Firms are classified into state-owned, foreign and private according to their register type.

Appendix Table A2—Patent applications at China's SIPO and patents applications at overseas patent offices to China-based applicants (1995–2014)

Year	Number of patent applications at China's SIPO	Distribution of patent applications by type of patents			Share of patent applications from outside China (%)	Number of applications at foreign patent offices by China-based applicants
		Invention (%)	Utility model (%)	Design (%)		
1995	83,045	26	53	21	17	224
1996	102,735	28	48	24	20	191
1997	114,208	29	44	27	21	394
1998	121,989	29	42	28	21	321
1999	134,239	27	43	30	18	397
2000	170,682	30	40	29	18	1,126
2001	203,573	31	39	30	19	2,323
2002	252,631	32	37	31	19	2,415
2003	308,487	34	35	30	19	1,811
2004	353,807	37	32	31	21	2,766
2005	476,264	36	29	34	20	3,432
2006	573,178	37	28	35	18	3,172
2007	693,917	35	26	39	15	3,602
2008	828,328	35	27	38	13	3,476
2009	976,686	32	32	36	10	5,535
2010	1,222,286	32	34	34	9	8,440
2011	1,633,347	32	36	32	8	10,097
2012	2,050,649	32	36	32	7	18,451
2013	2,377,061	35	37	38	6	25,712
2014	2,361,243	39	37	24	6	28,002
Annual growth rate in total number of patents in different periods (%)						
1995–2005	19	23	12	25	21	31
2005–2014	19	21	23	15	5	26
1995–2014	19	22	17	20	13	29

Note: Tabulated by authors based on aggregate data downloaded from China's State Intellectual Property Office's (SIPO's) webpage (http://www.sipo.gov.cn/tjxx/).

Appendix Table A3—Patents granted by China's SIPO and patents granted by overseas patent offices to China-based applicants (1995–2014)

Year	Number of patents granted by China's SIPO	Distribution of patents granted by type of patents			Share of patents granted to applicants from outside China (%)	Number of patents granted by foreign patent offices to China-based applicants
		Invention (%)	Utility model (%)	Design (%)		
1995	45,064	8	68	25	8	75
1996	43,780	7	62	31	9	52
1997	50,996	7	54	40	9	36
1998	67,889	7	50	43	10	47
1999	100,156	8	56	36	8	110
2000	105,345	12	52	36	10	88
2001	114,251	14	48	38	13	143
2002	132,399	16	43	40	15	192
2003	182,226	20	38	42	18	181
2004	190,238	26	37	37	20	282
2005	214,003	25	37	38	20	398
2006	268,002	22	40	38	16	636
2007	351,782	19	43	38	14	659
2008	411,982	23	43	34	14	860
2009	581,992	22	35	43	14	1,529
2010	814,825	17	42	41	9	2,587
2011	960,513	18	42	40	8	3,447
2012	1,255,138	17	46	37	7	4,887
2013	1,313,000	16	53	31	6	8,214
2014	1,302,687	18	54	28	7	10,603
Annual growth rate in total number of patents in different periods (%)						
1995–2005	17	31	10	22	28	18
2005–2014	22	18	27	18	9	44
1995–2014	19	25	18	20	18	30

Note: Tabulated by authors based on aggregate data downloaded from China's State Intellectual Property Office's (SIPO's) webpage (http://www.sipo.gov.cn/tjxx/).

Appendix Table A4—Total number of patents granted in the United States by USPTO to (corporate) applicants from BRICS, Germany, Japan, and the Republic of Korea

Year	China	Brazil	India	Russia	South Africa	Germany	Japan	Rep. of Korea
1995	62	63	37	98	123	6,600	21,764	1,161
1996	46	63	35	116	111	6,818	23,053	1,493
1997	62	62	47	111	101	7,008	23,179	1,891
1998	72	74	85	189	115	9,095	30,841	3,259
1999	90	91	112	181	110	9,337	31,104	3,562
2000	119	98	131	183	111	10,234	31,296	3,314
2001	195	110	177	234	120	11,260	33,223	3,538
2002	289	33	249	200	114	11,278	34,859	3,786
2003	297	130	341	202	112	11,444	35,517	3,944
2004	404	106	363	169	100	10,779	35,348	4,428
2005	402	77	384	148	87	9,011	30,341	4,352
2006	661	121	481	172	109	10,005	36,807	5,908
2007	772	90	546	188	82	9,051	33,354	6,295
2008	1,225	101	634	176	91	8,915	33,682	7,549
2009	1,655	103	679	196	93	9,000	35,501	8,762
2010	2,657	175	1,098	272	116	12,363	44,814	11,671
2011	3,174	215	1,234	298	123	11,920	46,139	12,262
2012	4,637	196	1,691	331	142	13,835	50,677	13,233
2013	5,928	254	2,424	417	161	15,498	51,919	14,548
2014	7,236	334	2,987	445	152	16,550	53,849	16,469
Annual growth rate in different periods (%)								
1995–2005	21	2	26	4	-3	3	3	14
2005–2014	38	18	26	13	6	7	7	16
1995–2014	28	9	26	8	1	5	5	15

Note: The figures stand for total number of patents granted to applicants from these countries by the U.S. Patent and Trademark Office (USPTO). Computed by authors based on data from World Intellectual Property Office (WIPO).

Appendix Table A5: Cross country comparison of number of patents, number of citations.

(coefficients on the interaction term between China and years are reported below)

Variables	Number of patents	Number of citations
China dummy* year of 1996	-0.404	
China dummy* year of 1997	-0.311	
China dummy* year of 1998	-0.295	
China dummy* year of 1999	-0.207	0.0607
China dummy* year of 2000	0.0323	0.0652
China dummy* year of 2001	0.404	0.901
China dummy* year of 2002	0.976*	1.508
China dummy* year of 2003	0.634	1.553
China dummy* year of 2004	1.053*	1.917*
China dummy* year of 2005	1.218**	2.193**
China dummy* year of 2006	1.497**	2.333**
China dummy* year of 2007	1.725***	2.981***
China dummy* year of 2008	2.084***	3.536***
China dummy* year of 2009	2.241***	3.327***
China dummy* year of 2010	2.391***	3.506***
China dummy* year of 2011	2.486***	
China dummy* year of 2012	2.727***	
China dummy* year of 2013	2.806***	
China dummy* year of 2014	2.876***	

Note: the second column shows the coefficients of China dummy * year from 1996 to 2014. The dependent variable for second column is number of patents approved in USPTO for each country in each year from WIPO (sample is 1995 to 2014), the independent variables includes country* year fixed effect for Germany, Japan, Korea and BRICS, log population, log population square, year fixed effect, and country fixed effect for other countries. The third column shows the coefficients of China dummy * year from 1999 to 2010. The dependent variable for third column is number of citations received of patents approved in USPTO for each country in each year based on US micro patent database (sample is 1998 to 2010), the independent variables are the same as those for second column.

Appendix Table A6— Citations by foreign patents on patents approved in SIPO by China's applicants (1995–2014)

Year	Invention patents	Utility patents
1995	100	65
1996	114	62
1997	174	100
1998	201	98
1999	244	125
2000	303	198
2001	522	357
2002	667	440
2003	1,019	681
2004	1,358	851
2005	1,765	1,089
2006	2,984	1,830
2007	5,087	2,721
2008	9,183	4,084
2009	13,347	5,097
2010	20,781	7,752
2011	30,706	11,241
2012	45,364	16,132
2013	55,649	21,072
2014	71,383	23,544
Annual growth rate in different periods (%)		
1995–2004	34	33
2004–2014	49	39
1995–2014	41	36

Note: Tabulated by authors based on citations from Google Patent System.

Appendix Table A7—Hybrid negative binomial regressions on patent count: Baseline

VARIABLES	(1) Total	(2) Invention	(3) Utility	(4) Design
Sales (log)	0.437***	0.491***	0.435***	0.424***
	(0.012)	(0.024)	(0.015)	(0.019)
Export	0.115***	0.181***	0.071**	0.157***
	(0.022)	(0.045)	(0.028)	(0.036)
Wage (log)	0.082***	0.224***	0.137***	0.072*
	(0.027)	(0.050)	(0.034)	(0.042)
Subsidy rate (log)	0.003	0.045***	0.003	0.010
	(0.006)	(0.011)	(0.007)	(0.009)
Tax rate (log)	-0.073***	-0.066**	-0.085***	-0.036
	(0.017)	(0.032)	(0.021)	(0.027)
Interest rate (log)	-0.025**	0.010	-0.042***	-0.036**
	(0.010)	(0.020)	(0.013)	(0.016)
Partner tariff	-1.048***	-0.843***	-1.123***	-0.482***
	(0.078)	(0.146)	(0.115)	(0.118)
HH index	0.143	-0.087	0.541**	0.358
	(0.224)	(0.425)	(0.267)	(0.328)
Observations	1,187,140	1,187,140	1,187,140	1,187,140
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
AIC	438522	114137	270400	213959

Note: *Wage* (log), *Subsidy rate* (log), *Tax rate* (log), *Interest rate* (log) are averages at the city-industry-firm ownership type-year level (except for the firm itself). Cells with fewer than six observations are dropped. *Sales* (log) and *Export* are still firm-year level.

Appendix Table A8—Hybrid negative binomial regression on patent count: Using lagged wages

VARIABLES	(1) Total	(2) Invention	(3) Utility	(4) Design
Sales (log)	0.419***	0.454***	0.418***	0.416***
	(0.013)	(0.026)	(0.016)	(0.021)
Export	0.119***	0.172***	0.065**	0.161***
	(0.025)	(0.049)	(0.031)	(0.041)
Lag wage (log)	0.510***	0.890***	0.790***	0.541***
	(0.058)	(0.113)	(0.074)	(0.090)
Subsidy rate (log)	-0.007	0.033***	-0.009	-0.003
	(0.006)	(0.012)	(0.008)	(0.010)
Tax rate (log)	-0.067***	-0.057	-0.080***	-0.036
	(0.020)	(0.036)	(0.025)	(0.032)
Interest rate (log)	-0.018	0.017	-0.034**	-0.031*
	(0.011)	(0.021)	(0.014)	(0.019)
Partner tariff	-0.850***	-0.314*	-0.666***	-0.454***
	(0.091)	(0.171)	(0.131)	(0.140)
HH index	0.238	-0.092	0.622**	0.337
	(0.240)	(0.429)	(0.279)	(0.361)
Observations	984,517	984,517	984,517	984,517
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
AIC	368333	99218	229716	173836

Note: See Table A2. The value of wage variable is lagged by one year.

Appendix Table A9— Hybrid negative binomial regression on patent count: Using minimum wages

VARIABLES	(1) Total	(2) Invention	(3) Utility	(4) Design
Sales (log)	0.430***	0.441***	0.434***	0.435***
	(1.126)	(2.186)	(1.424)	(1.793)
Export	0.104***	0.172***	0.065**	0.148***
	(2.208)	(4.351)	(2.772)	(3.559)
Minimum wage (log)	0.318***	0.484***	0.607***	0.371***
	(4.890)	(9.569)	(6.354)	(7.597)
Subsidy rate (log)	-0.003	0.017*	-0.005	-0.013
	(0.526)	(0.978)	(0.664)	(0.859)
Tax rate (log)	0.050**	0.115***	0.026	0.053*
	(1.994)	(3.774)	(2.523)	(3.130)
Interest rate (log)	-0.012	-0.006	-0.040***	0.014
	(1.140)	(2.277)	(1.407)	(1.829)
Partner tariff	-9.156***	-6.279**	-8.354***	-4.772***
	(112.564)	(258.170)	(184.781)	(127.120)
HH index	0.358	0.085	0.486*	0.517
	(21.901)	(38.670)	(26.178)	(33.429)
Observations	1,305,376	1,305,376	1,305,376	1,305,376
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
AIC	461094	124633	283566	217422

Note: See Table A2. Minimum wages are at the city and year level.

Appendix Table A10—Impact of wage on innovations of labor intensive firms

VARIABLES	(1) Total	(2) Invention	(3) Utility	(4) Design
Wage (log)*Labor intensive dummy	0.163***	0.695***	-0.042	0.174***
	(0.038)	(0.073)	(0.052)	(0.059)
Sales (log)	0.436***	0.483***	0.433***	0.425***
	(0.012)	(0.024)	(0.015)	(0.019)
Export	0.108***	0.162***	0.064**	0.153***
	(0.022)	(0.045)	(0.028)	(0.036)
Wage (log)	0.010	-0.101*	0.184***	0.007
	(0.034)	(0.061)	(0.050)	(0.051)
Subsidy rate (log)	0.006	0.044***	0.008	0.012
	(0.006)	(0.011)	(0.007)	(0.009)
Tax rate (log)	-0.068***	-0.032	-0.082***	-0.031
	(0.017)	(0.033)	(0.021)	(0.027)
Interest rate (log)	-0.022**	0.021	-0.040***	-0.035**
	(0.011)	(0.020)	(0.013)	(0.017)
Partner tariff	-1.138***	-1.091***	-1.141***	-0.475***
	(0.082)	(0.148)	(0.120)	(0.122)
HH index	0.260	-0.090	0.597**	0.456
	(0.223)	(0.423)	(0.265)	(0.327)
Observations	1,187,140	1,187,140	1,187,140	1,187,140
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
AIC	436557	114023	266115	213652

Note: The dependent variable is patent count. Hybrid negative binomial regression is used. See Qu et al. (2013) for the definition of labor-intensive industries.

Appendix Table A11—Impact of wages on innovations in routine-intensive industries and sunset industries

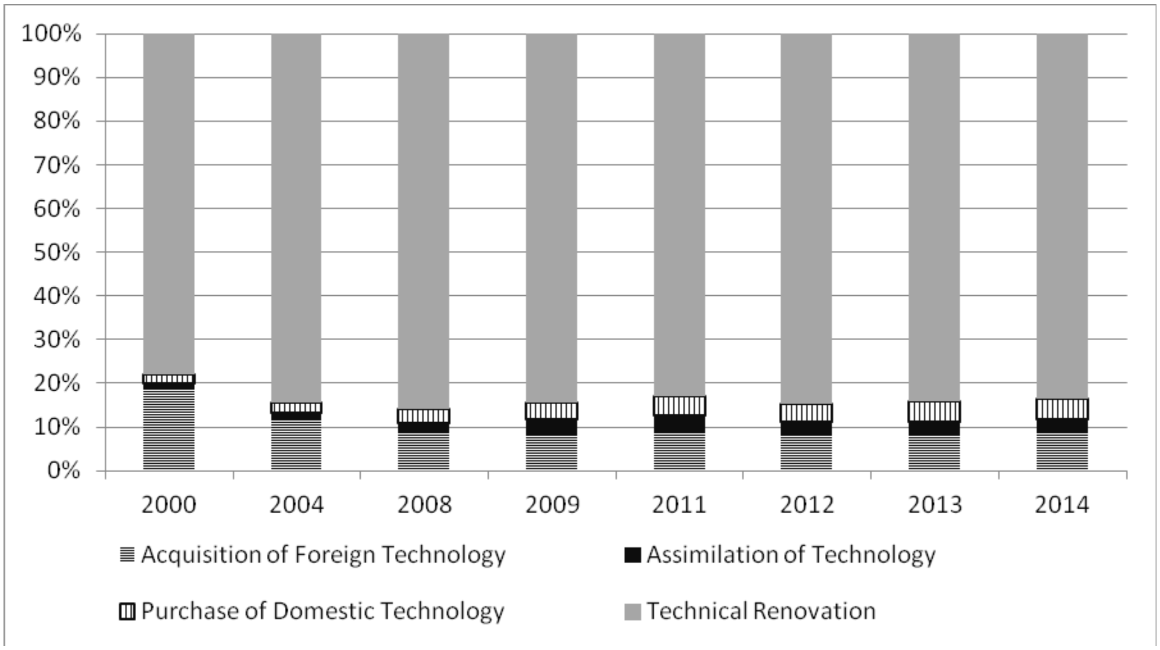
	(1)	(2)	(3)	(4)
VARIABLES	Total	Invention	Utility	Design
Panel A: Impact on routine-intensive industries				
Wage (log)*Routine	0.490***	0.992***	0.237***	0.759***
	(0.048)	(0.089)	(0.082)	(0.072)
Panel B: Impact on sunset industries				
Wage (log)*Sunset	0.040	-0.222***	-0.058	0.089
	(0.040)	(0.072)	(0.052)	(0.064)

Note: Hybrid negative binomial regression estimates. Routine industry is defined according to Autor et al. (2003).

Appendix Table A12—Impact of R&D on Patent Output: **Hybrid negative binomial regressions**

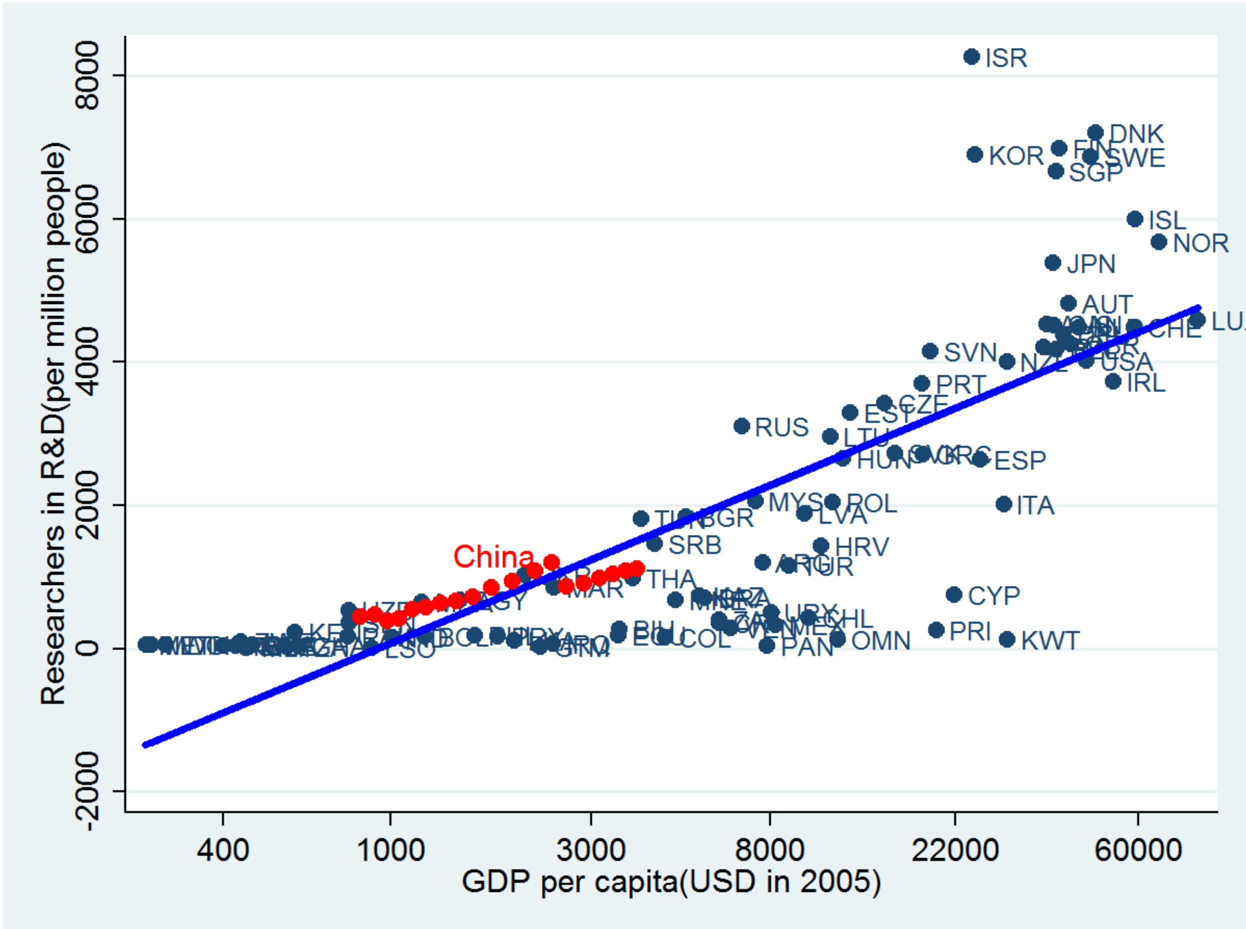
	(1)	(2)	(3)	(4)
VARIABLES	Total	Invention	Utility model	Design
R&D (log)*FIE	-0.006*	-0.006	0.002	-0.016**
	(0.004)	(0.006)	(0.004)	(0.006)
R&D (log)*SOE	-0.011**	-0.020***	-0.004	-0.016
	(0.005)	(0.007)	(0.005)	(0.010)
R&D (log)	0.015***	0.017***	0.013***	0.012***
	(0.002)	(0.004)	(0.003)	(0.004)
Sales (log)	0.274***	0.328***	0.254***	0.287***
	(0.022)	(0.039)	(0.027)	(0.036)
Observations	785,235	785,235	785,235	785,235
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
AIC	300800	93583	192008	136310

Note: Since R&D data is only available for 2005–2007, we include only these three years' data in the sample.



Appendix Figure A1—Declining Contribution of Imported Foreign technology: Evidence from Above-scale Manufacturing Firms

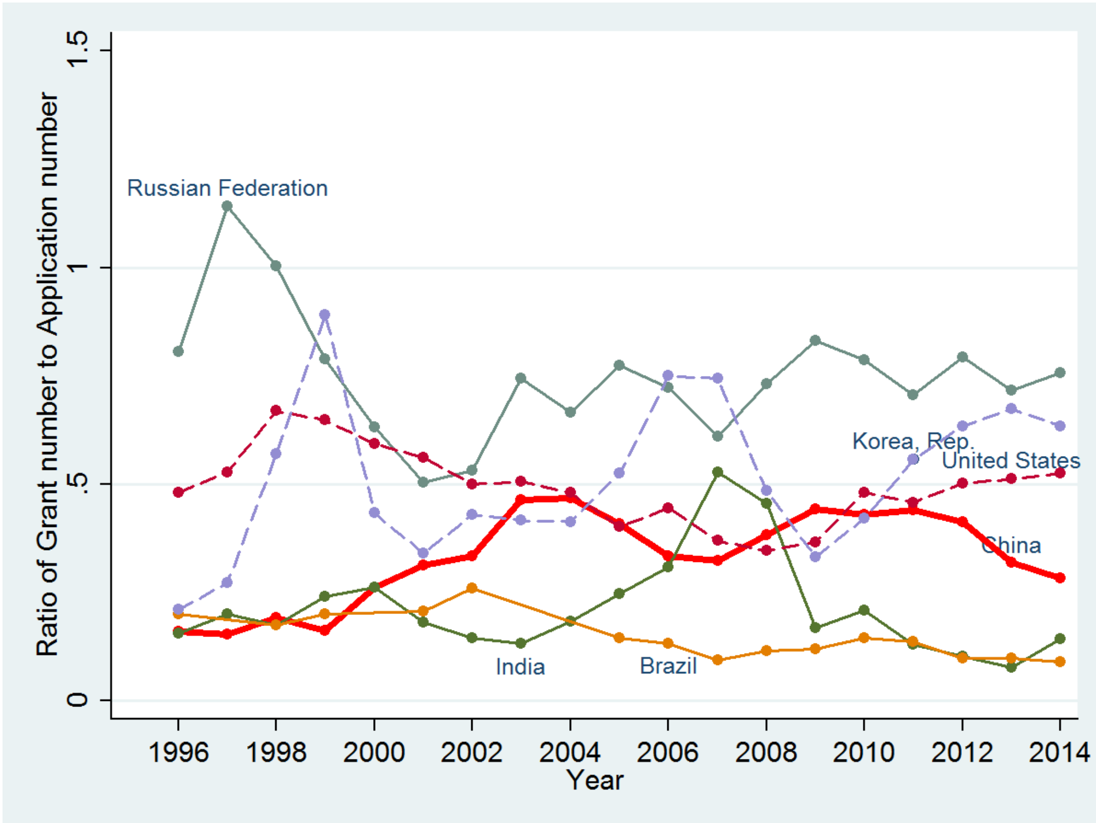
Source: China Statistical Yearbook on Science and Technology (China National Bureau of Statistics, various years).



Appendix Figure A2—Researcher Intensity Comparison

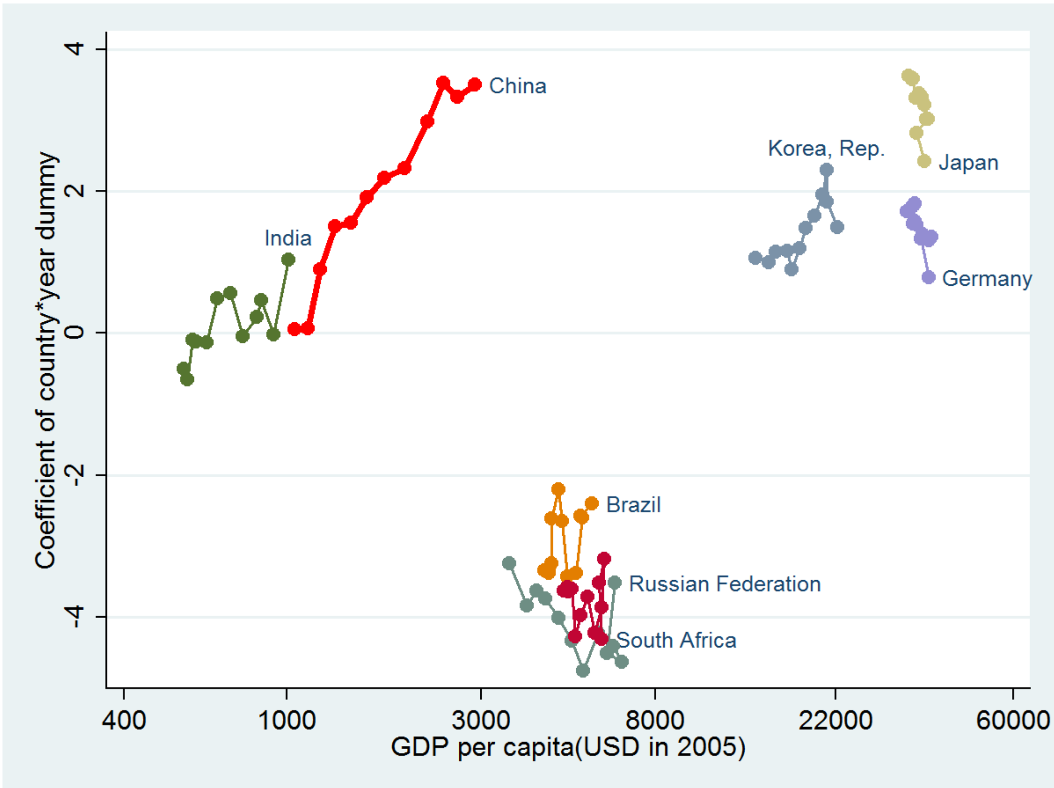
Note: Chinese data is from 1996 to 2014. For all other countries, the sample is for 2014 or the latest year available (not later than 2010). China adjusted the statistical coverage since 2009, so we see a sudden drop for China (red points in graph).

Source: World Bank.



Appendix Figure A3—Patent Approval Rate in BRIC Countries, the Republic of Korea, and the U.S.

Source: WIPO. The approval rate is defined as # patents granted in year t / # applications in year t-1.



Appendix Figure 4—Forward Citations of Patents Granted by USPTO: Cross-country Comparison

Note: Conditional plot by controlling for population, population squared, and country and year fixed effects, based on data of USPTO (1998-2010).