Online Appendix: In Search of Labor Demand

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In this appendix, we discuss our data construction in section A, additional minimum wage results in section B, the implementation of the selection correction procedure described in the main text in section C, our correction for our standard errors to deal with the generated regressor in section D, an extension to the model to allow for national level search by entrepreneurs in section E, and alternative estimates in section F.

Data

A1. U.S. Census and American Community Survey

The Census data was obtained with extractions done using the IPUMS system (see Ruggles et al. (2015)). The files were the 1980 5% State (A Sample), 1990 State, 2000 5% Census PUMS, and the 2007 American Community Survey. For 1970, Forms 1 and 2 were used for the Metro sample. The initial extraction includes all individuals aged 20 - 65 not living in group quarters. All calculations are made using the sample weights provided. For the 1970 data, we adjust the weights for the fact that we combine two samples. We focus on the log of weekly wages, calculated by dividing wage and salary income by annual weeks worked. We impute incomes for top coded values by multiplying the top code value in each year by 1.5. Since top codes vary by State in 1990 and 2000, we impose common top-code values of 140,000 in 1990 and 175,000 in 2000.

A consistent measure of education is not available for these Census years. We use indicators based on the IPUMS recoded variable `EDUCREC` that computes comparable categories from the 1980 Census data on years of school completed and later Census years that report categorical schooling only. To calculate potential experience (age minus years of education minus six), we assign group mean years of education from Table 5 in Park (1994) to the categorical education values reported in the 1990 and 2000 Censuses.

Census definitions of metropolitan areas are not comparable over time since, in general, the geographic areas covered by them increase over time and their definitions are updated to reflect this expansion. The definition of cities we use

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attempts to maximize geographic comparability over time and roughly correspond to 1990 definitions of MSAs provided by the U.S. Office of Management and Budget.[1] To create geographically consistent MSAs, we follow a procedure based largely on Deaton and Lubotsky (2003) which uses the geographical equivalency files for each year to assign individuals to MSAs or PMSAs based on FIPs state and PUMA codes (in the case of 1990 and 2000) and county group codes (for 1970 and 1980). Each MSA label we use is essentially defined by the PUMAs it spans in 1990. Once we have this information, the equivalency files dictate what counties to include in each city for the other years. Since the 1970 county group definitions are much courser than those in later years, the number of consistent cities we can create is dictated by the 1970 data. This process results in our having 152 MSAs that are consistent across all our sample years. Code for this exercise was generously provided by Ethan G. Lewis. Our definitions differ slightly from those in Deaton and Lubotsky (2003) in order to improve the 1970-1980-1990-2000 match.

We use an industry coding that is consistent across Censuses and is based on the IPUMS recoded variable `IND1950`, which recodes census industry codes to the 1950 definitions. This generates 144 consistent industries.[2] We have also replicated our results using data only for the period 1980 to 2000, where we can use 1980 industry definitions to generate a larger number of consistent industry categories.[3] We are also able to define more (231) consistent cities for that period.

A2. Current Population Survey

Our minimum wage application uses data from the Current Population Survey. The main source of the data is the Outgoing Rotation Group for the survey years 2011-2014 downloaded from the NBER.[4] Our extractions included all individuals between the ages of 16-64.

The construction of our wage data closely follows Lemieux (2006). Wage data is based on those who report employment in reference week. In all wage calculations, we set allocated wages to missing. Our hourly wage measure is based on reported hourly wage for those who report hourly payment and not adjusted for topcoding. For workers who are not paid hourly we adjust for topcoded wages by a factor of 1.4 and divide the result by usual hours worked per week. For all wage data, we Winsorize hourly wages below the minimum wage and greater than 100. All wage figures are in 2014 dollars. For all reported wage statistics, we construct a 'labor supply weight' by multiplying the usual weight in the ORG CPS by usual hours

[1] See http://www.census.gov/population/estimates/pastmetro.html for details.

[2] See http://usa.ipums.org/usa-action/variableDescription.do?mnemonic=IND1950 for details.

[3] The program used to convert 1990 codes to 1980 comparable codes is available at http://www.trinity.edu/bhirsch/unionstats . That site is maintained by Barry Hirsch, Trinity University and David Macpherson, Florida State University. Code to convert 2000 industry codes into 1990 codes was provided by Chris Wheeler and can be found at http://research.stlouisfed.org/publications/review/past/2006. See also a complete table of 2000-1990 industry crosswalks at http://www.census.gov/hhes/www/ioindex/indcswk2k.pdf

[4] Links are http://www.nber.org/data/cps_may.html and http://www.nber.org/data/morg.html

divided by 35. Our metro areas use the Core based statistical areas definitions from the NBER extract.

In order to match minimum wage changes to workers, we require a measure of firm size. To do this, we use the Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS), downloaded from IPUMS-CPS (Flood et al., 2015), and match these data with our ORG data using the procedure outlined in Pacas and Flood (2015).

A3. Quarterly Census of Employment and Wages

Our establishment data comes from the Quarterly Census of Employment and Wages annual county files for the years 1975-2015. It reports establishment counts based on county and industry, subject to disclosure limitations to prevent the release of identifying information regarding single establishments. SIC 2-digit level industrial classifications are available from 1975-2000 and NAICS 4-digit level industrial classifications are available from 1990-2015.

1) As a first-step, we convert QCEW data into industrial classifications matching the Census:
    a) For the years 1975-2000, we extract the QCEW by 2-digit SIC code. These codes are converted into Census classifications based on our own crosswalk. In some cases, SIC industries must be split across Census industrial codes, and this is done based on employment in the Census.
    b) For the years 2000-2015, we extract the QCEW based on NAICs codes. This is done based on the crosswalks provided by the Census Bureau.[5]
    c) Our final data set uses decadel changes in the log number of establishments. We compute this using data based on SIC codes for the 1970s, 1980s, and 1990s and using NAICS for 2000-2007 and 2007-2015, and thus avoid differencing between any two years based on different industrial classifications.
2) As a second-step, we convert the county-level data to SMSA level data. The first, we convert counties to PUMAS using crosswalks provided by the Missouri Data Center.[6] We then convert the data to our SMSA-level definitions based on PUMA and state.

Additional Minimum Wage Results

Minimum Wage Demographic Impact

[5]Available from https://www.census.gov/people/io/methodology/

[6]We use http://mcdc.missouri.edu/websas/geocorr14.html for post 2010 data, http://mcdc.missouri.edu/websas/geocorr2k.html for 2000 and 2007, and http://mcdc.missouri.edu/websas/geocorr90.shtml for prior Census years.

	Seattle		San Francisco		Los Angeles	
	Near Current	Near 15	Near Current	Near 15	Near Current	Near 15
Teenager	0.17	0.01	0.11	0.02	0.08	0.01
Restaurants	0.30	0.10	0.24	0.06	0.20	0.05
Female	0.52	0.58	0.52	0.63	0.52	0.45
Non White	0.27	0.20	0.39	0.36	0.20	0.25
Drop Out	0.23	0.08	0.30	0.12	0.33	0.19
High School	0.26	0.27	0.25	0.21	0.29	0.32
BA	0.13	0.25	0.15	0.25	0.11	0.18

Notes: Each entry in the table is the fraction of each demographic group located within 1 dollar from the current minimum wage or between 14-15 dollars for the indicated city. To calculate this fraction near the 15 dollar value, we inflate wages by 2 percent per year up until the year that the minimum wage reaches 15 dollars in nominal terms.

B1. Los Angeles

Table B1—Wage Impact from Minimum Wage changes – Los Angeles

	(1) 2016	(2) 2017	(3) 2018	(4) 2019	(5) 2020	(6) 2021
(1) Initial	2.85*	2.87*	2.91*	2.95*	2.98*	3.00*
	(0.0090)	(0.0088)	(0.0082)	(0.0078)	(0.0074)	(0.0072)
(2) Direct Impact	0.018*	0.042*	0.036*	0.030*	0.023*	0.019*
	(0.00058)	(0.00098)	(0.00075)	(0.00060)	(0.00045)	(0.0012)
(3) End-of-Year	2.87*	2.91*	2.95*	2.98*	3.00*	3.02*
	(0.0088)	(0.0082)	(0.0078)	(0.0074)	(0.0072)	(0.0069)
(4) Fraction Impacted	0.17*	0.27*	0.32*	0.36*	0.38*	0.42*
	(0.0051)	(0.0060)	(0.0065)	(0.0066)	(0.0067)	(0.0070)
Total Wage Change						0.171
s.e.						0.003

Notes: Wage Impacts calculated as follows: Row (1) gives the average log wage at the beginning of the period. Row (2) gives the impact on the average log wage caused by the period's minimum wage increase. Row (3) gives the end-of-year average log wage ((1) + (2)). Row (4) gives the cumulative fraction of workers impacted by the roll-out of the minimum wage policy. All wage figures are in 2014 dollars.

Table B2—Employment Impacts from Minimum Wage Changes – Los Angeles

	(1) 2016	(2) 2017	(3) 2018	(4) 2019	(5) 2020	(6) 2021
(1) Initial	64.0*	63.6*	62.8*	62.1*	61.5*	61.0*
	(0.49)	(0.51)	(0.65)	(0.84)	(1.01)	(1.14)
(2) Wage Only	-1.14*	-3.38*	-4.68*	-5.67*	-6.36*	-6.91*
	(0.18)	(0.52)	(0.78)	(1.01)	(1.18)	(1.32)
(3) Congestion + (2)	-0.36*	-0.84*	-0.72*	-0.59*	-0.45*	-0.36*
	(0.13)	(0.30)	(0.25)	(0.20)	(0.15)	(0.12)
(4) End-of-Year	63.6*	62.8*	62.1*	61.5*	61.0*	60.7*
	(0.51)	(0.65)	(0.84)	(1.01)	(1.14)	(1.24)
Total Emp. Change						-3.32
s.e.						1.14

Notes: Employment Impacts calculated as follows: Row (1) gives the employment rate at the beginning of the period. Row (2) gives the first round effect on the employment rate ($\beta_1 \times \Delta w_{ict}$, summed over industries). Row (3) gives the employment effect taking into account congestion effects ($\frac{\beta_1}{1-\beta_3} \times \Delta w_{ct}$)). Row (4) gives the end-of-year employment rate.

Table B3—Wage impacts by Sector from Minimum Wage Changes – Los Angeles

	(1) 2014	(2) 2016	(3) 2017	(4) 2018	(5) 2019	(6) 2020	(7) 2021	(8) Total
Agriculture, Mining, Cons.	2.87*	0.0078*	0.027*	0.028*	0.027*	0.022*	0.027*	0.14*
	(0.036)	(0.0019)	(0.0036)	(0.0031)	(0.0026)	(0.0020)	(0.0059)	(0.013)
Manufacturing	2.84*	0.020*	0.045*	0.038*	0.032*	0.025*	0.017*	0.18*
	(0.024)	(0.0016)	(0.0028)	(0.0021)	(0.0016)	(0.0011)	(0.0029)	(0.0083)
Transport, Com., Util.	3.01*	0.011*	0.028*	0.024*	0.022*	0.017*	0.0090*	0.11*
	(0.033)	(0.0015)	(0.0030)	(0.0023)	(0.0018)	(0.0013)	(0.0031)	(0.0097)
Retail, Wholesale	2.65*	0.028*	0.058*	0.049*	0.040*	0.030*	0.024*	0.23*
	(0.019)	(0.0019)	(0.0027)	(0.0020)	(0.0015)	(0.0011)	(0.0038)	(0.0084)
F.I.R.E	3.06*	0.0078*	0.022*	0.022*	0.019*	0.016*	0.011*	0.098*
	(0.033)	(0.0017)	(0.0031)	(0.0025)	(0.0019)	(0.0014)	(0.0031)	(0.010)
Personal, Enter.	2.51*	0.033*	0.077*	0.064*	0.052*	0.039*	0.036*	0.30*
	(0.017)	(0.0020)	(0.0030)	(0.0020)	(0.0015)	(0.0011)	(0.0041)	(0.0081)
Professional	2.99*	0.012*	0.030*	0.027*	0.024*	0.019*	0.015*	0.13*
	(0.015)	(0.00087)	(0.0015)	(0.0012)	(0.00089)	(0.00065)	(0.0017)	(0.0049)

Notes: Wage impacts by sector. Bootstrap standard errors in parentheses. The first column shows the wage in the sector at the onset of the policy. The rest of the columns show the change in the average log wage in the sector induced by the minimum wage policy implementation from one year to the next.

TABLE B4—EMPLOYMENT RATE BY SECTOR AND MINIMUM WAGE ROLL-OUT – LOS ANGELES

	(1) 2014	(2) 2016	(3) 2017	(4) 2018	(5) 2019	(6) 2020	(7) 2021	(8) Total
Agriculture, Mining, Cons.	3.78	3.76	3.71	3.66	3.61	3.57	3.52	-0.26
	(0.21)	(0.21)	(0.22)	(0.23)	(0.24)	(0.25)	(0.27)	(0.19)
Manufacturing	7.73	7.50	7.00	6.61	6.31	6.09	5.93	-1.80
	(0.28)	(0.28)	(0.34)	(0.41)	(0.47)	(0.51)	(0.55)	(0.51)
Transport, Com., Util.	5.33	5.26	5.09	4.94	4.82	4.72	4.67	-0.65
	(0.24)	(0.24)	(0.25)	(0.28)	(0.31)	(0.34)	(0.36)	(0.29)
Retail, Wholesale	8.91	8.72	8.32	8.00	7.75	7.58	7.43	-1.48
	(0.34)	(0.34)	(0.38)	(0.43)	(0.48)	(0.52)	(0.55)	(0.44)
F.I.R.E	4.62	4.59	4.50	4.41	4.33	4.27	4.23	-0.40
	(0.23)	(0.23)	(0.23)	(0.23)	(0.24)	(0.24)	(0.25)	(0.13)
Personal, Enter.	9.82	9.51	8.80	8.25	7.84	7.55	7.29	-2.53
	(0.35)	(0.34)	(0.40)	(0.48)	(0.55)	(0.60)	(0.65)	(0.63)
Professional	23.8	23.5	22.8	22.2	21.8	21.4	21.1	-2.75
	(0.44)	(0.45)	(0.56)	(0.71)	(0.86)	(0.97)	(1.05)	(0.97)

Notes: Employment rate by sector. Employment rate is calculated as as employment divided by working-age population Each entry is the employment rate in an industry aggregate after policy year t. Bootstrap standard errors in parentheses.

B2. San Francisco

Table B5—Wage Impact from Minimum Wage changes – San Francisco

	(1) 2015	(2) 2016	(3) 2017	(4) 2018	(5) 2019
(1) Initial	3.18*	3.19*	3.21*	3.22*	3.24*
	(0.016)	(0.016)	(0.016)	(0.015)	(0.015)
(2) Direct Impact	0.0015*	0.019*	0.013*	0.018*	0.013*
	(0.000082)	(0.00100)	(0.00063)	(0.00080)	(0.00069)
(3) End-of-Year	3.19*	3.21*	3.22*	3.24*	3.25*
	(0.016)	(0.016)	(0.015)	(0.015)	(0.014)
(4) Fraction Impacted	0.16*	0.20*	0.21*	0.23*	0.25*
	(0.0088)	(0.0099)	(0.010)	(0.010)	(0.010)
Total Wage Change					0.067
s.e.					0.003

Notes: Wage Impacts calculated as follows: Row (1) gives the average log wage at the beginning of the period. Row (2) gives the impact on the average log wage caused by the period's minimum wage increase. Row (3) gives the end-of-year average log wage ((1) + (2)). Row (4) gives the cumulative fraction of workers impacted by the roll-out of the minimum wage policy. All wage figures are in 2014 dollars.

Table B6—Employment Impacts from Minimum Wage Changes – San Francisco

	(1) 2015	(2) 2016	(3) 2017	(4) 2018	(5) 2019
(1) Initial	69.1*	69.1*	68.7*	68.4*	68.0*
	(0.88)	(0.88)	(0.89)	(0.92)	(0.99)
(2) Wage Only	-0.095*	-1.32*	-1.76*	-2.60*	-3.05*
	(0.027)	(0.22)	(0.34)	(0.51)	(0.65)
(3) Congestion + (2)	-0.030*	-0.40*	-0.27*	-0.36*	-0.27*
	(0.015)	(0.19)	(0.13)	(0.17)	(0.13)
(4) End-of-Year	69.1*	68.7*	68.4*	68.0*	67.8*
	(0.88)	(0.89)	(0.92)	(0.99)	(1.05)
Total Emp. Change					-1.33
s.e.					0.63

Notes: Employment Impacts calculated as follows: Row (1) gives the employment rate at the beginning of the period. Row (2) gives the first round effect on the employment rate ($\beta_1 \times \Delta w_{ict}$, summed over industries). Row (3) gives the employment effect taking into account congestion effects ($\frac{\beta_1}{1-\beta_3} \times \Delta w_{ct}$)). Row (4) gives the end-of-year employment rate.

Table B7—Wage impacts by Sector from Minimum Wage Changes – San Francisco

	(1) 2014	(2) 2015	(3) 2016	(4) 2017	(5) 2018	(6) 2019	(7) Total
Agriculture, Mining, Cons.	3.06*	0.0014*	0.019*	0.013*	0.019*	0.010*	0.063*
	(0.056)	(0.00034)	(0.0043)	(0.0026)	(0.0035)	(0.0027)	(0.012)
Manufacturing	3.39*	0.0010*	0.013*	0.0090*	0.013*	0.012*	0.048*
	(0.058)	(0.00022)	(0.0027)	(0.0018)	(0.0023)	(0.0022)	(0.0084)
Transport, Com., Util.	3.29*	0.0011*	0.013*	0.0079*	0.011*	0.011*	0.045*
	(0.059)	(0.00027)	(0.0032)	(0.0019)	(0.0025)	(0.0023)	(0.0097)
Retail, Wholesale	2.94*	0.0024*	0.032*	0.021*	0.029*	0.023*	0.11*
	(0.041)	(0.00027)	(0.0033)	(0.0020)	(0.0026)	(0.0022)	(0.0094)
F.I.R.E	3.47*	0.00031*	0.0043*	0.0039*	0.0060*	0.0064*	0.021*
	(0.050)	(0.00014)	(0.0017)	(0.0013)	(0.0018)	(0.0017)	(0.0062)
Personal, Enter.	2.65*	0.0043*	0.055*	0.036*	0.047*	0.031*	0.17*
	(0.030)	(0.00028)	(0.0034)	(0.0020)	(0.0025)	(0.0025)	(0.0093)
Professional	3.34*	0.00066*	0.0099*	0.0077*	0.010*	0.0077*	0.036*
	(0.022)	(0.000089)	(0.0011)	(0.00077)	(0.00098)	(0.00079)	(0.0034)

Notes: Wage impacts by sector. Bootstrap standard errors in parentheses. The first column shows the wage in the sector at the onset of the policy. The rest of the columns show the change in the average log wage in the sector induced by the minimum wage policy implementation from one year to the next.

Table B8—Employment Rate by Sector and Minimum Wage Roll-out – San Francisco

	(1) 2014	(2) 2015	(3) 2016	(4) 2017	(5) 2018	(6) 2019	(7) Total
Agriculture, Mining, Cons.	4.20	4.20	4.16	4.13	4.09	4.07	-0.13
	(0.38)	(0.38)	(0.38)	(0.38)	(0.39)	(0.39)	(0.10)
Manufacturing	5.37	5.36	5.26	5.19	5.10	5.00	-0.37
	(0.46)	(0.46)	(0.46)	(0.46)	(0.45)	(0.45)	(0.13)
Transport, Com., Util.	5.37	5.36	5.28	5.23	5.16	5.10	-0.28
	(0.44)	(0.44)	(0.43)	(0.43)	(0.43)	(0.43)	(0.13)
Retail, Wholesale	8.20	8.18	7.98	7.85	7.67	7.53	-0.66
	(0.51)	(0.51)	(0.51)	(0.50)	(0.51)	(0.52)	(0.21)
F.I.R.E	5.61	5.61	5.59	5.57	5.54	5.51	-0.11
	(0.43)	(0.43)	(0.43)	(0.43)	(0.42)	(0.42)	(0.046)
Personal, Enter.	9.67	9.63	9.12	8.81	8.41	8.16	-1.51
	(0.59)	(0.58)	(0.57)	(0.57)	(0.60)	(0.62)	(0.41)
Professional	30.7	30.7	30.4	30.1	29.8	29.6	-1.06
	(0.90)	(0.90)	(0.90)	(0.91)	(0.93)	(0.95)	(0.41)

Notes: Employment rate by sector. Employment rate is calculated as as employment divided by working-age population Each entry is the employment rate in an industry aggregate after policy year t. Bootstrap standard errors in parentheses.

Selection Correction

The approach we use to address the issue of selection on unobservables of workers across cities follows Dahl (2002). Dahl argues that, under a sufficiency assumption, the selection-related error mean term in the wage equation for individual i can be expressed as a flexible function of the probability that a person born in i's state of birth actually chooses to live in city c in each Census year.[7] Dahl's approach is a two-step procedure that first requires estimates of the probability that i made the observed choice and then adds functions of these estimates into the wage equation to proxy for the error mean term. Dahl also presents a flexible method of estimating the migration probabilities that groups individuals based on observable characteristics and uses mean migration flows as the probability estimates. We closely follow Dahl's procedure aside from several small changes to account for the fact that we use cities rather than states and to account for the location of foreign born workers.

Dahl's approach first groups observations based on whether they are "stayers" or "movers". Dahl defines stayers as individuals that reside in their state of birth in the Census year. Since we use cities instead of states, we define stayers as those individuals that reside in a city that is at least partially located in individual's state of birth in a given Census year. Movers are defined as individuals that reside in a city that is not located in that individual's state of birth in a given Census year. We also retain foreign born workers, whereas Dahl drops them. For these workers, we essentially treat them as "movers" and use their country of origin as their "state of birth".[8] Within the groups defined as stayers, movers, and immigrants, we additionally divide observations based on gender, education (4 groups), age (5 groups), black, and hispanic indicators. Movers are further divided by state of birth. For stayers, we further divide the cells based on family characteristics.[9] Immigrants are further divided into cells based on country of origin as described above.

As in Dahl (2002), we estimate the relevant migration probabilities using the proportion of people within cells, defined above, who made the same move or stayed in their birth state. For each group, we calculate the probability that an individual made the observed choice and for movers, we follow Dahl in also calculating the retention probability (i.e. the probability that individual i was born in a given state, and remained in a city situated at least partly in that state in general). For movers, the estimated probabilities that individuals are observed in city c in year t differ based on individuals' state of birth (and other observable characteristics). Thus, identification of the error mean term comes from the

[7] This sufficiency assumption essentially says that knowing the probability of an individual's observed or "first-best" choice is all that is relevant for determining the selection effect, and that the probabilities of choices that were not made do not matter in the determination of ones wage in the city where they actually locate.

[8] We use the same country of origin groups as for the enclave instrument.

[9] Specifically, we use single, married without children, and married with at least one child under the age of 5.

assumption that the state of birth does not affect the determination of individual wages, apart from through the selection term. For stayers, identification comes from differences in the probability of remaining in a city in ones birth state for individuals with different family circumstances. For immigrants, we assign the probability that an individual was observed in city c in a given Census year using the probabilities from immigrants with the same observable characteristics in the preceding Census year.[10] This follows the type of ethnic enclave assumption used in several recent papers on immigration, essentially using variation based on the observation that immigrants from a particular region tend to migrate to cities where there are already communities of people with their background.

Having estimated the observed choice or "first-best" choice of stayers, movers, and immigrants and the retention probability for movers, we can then proceed to the second step in adjusting for selection bias. To do this, we add functions of these estimated probabilities into the first stage individual-level regressions used to calculate regression adjusted average city-industry wages. For movers, we add a quadratic of the probability that an observationally similar individual was born in a given state and was observed in a given city and a quadratic of the probability that an observationally similar individual stayed in their birth state. For stayers, we add a quadratic of the probability that an individual remained in their state of birth. For immigrants, we add a quadratic of the probability that an similar individual was observed in a given city in the preceding Census year. Dahl allows the coefficients on these functions to differ by state, whereas we assume that they are the same across all cities.

Correcting Standard Errors for Generated Wage Regressor

D1. Outline of Procedure

First-stage regression adjustment:

$$\ln w_{jict} = \mathbf{x}_{jict}\alpha_t + \nu_{ict} + e_{jict}$$

Where indexes j,i,c and t are person, industry, city and year. We estimate $\hat{\nu}_{ict}$, regression-adjusted city-industry wage premia, and $\hat{\nu}_{jt} = \bar{\hat{\nu}}_{ict} = \frac{1}{C}\sum_c \hat{\nu}_{ict}$, the national-level wage premia.

The Second-step OLS estimates:
Our main estimating equation is given by,

$$\Delta \ln \frac{E_{ict}}{L_{ct}} = d_{jt} + \beta_1 \Delta\nu_{ict} + \beta_3 \Delta \ln \frac{E_{ict}}{L_{ct}} + \beta_2 \Delta \ln L_{ct} + \Delta\epsilon_{ict}$$

[10]For cities in the 1980 Census not observed in the 1970 Census, we use the 1980 probabilities.

But $\Delta\nu_{jct}$ is not observed, thus we use our estimate. Substitution yields:

$$\Delta \ln \frac{E_{ict}}{L_{ct}} = d_{jt} + \beta_1 \Delta\hat{\nu}_{ict} + \beta_3 \Delta \ln \frac{E_{ict}}{L_{ct}} + \beta_2 \Delta \ln L_{ct} + \Delta\epsilon_{ict} + \beta_1(\Delta\nu_{ict} - \Delta\hat{\nu}_{ict})$$

or,

$$\begin{aligned}\Delta \ln \frac{E_{ict}}{L_{ct}} &= d_{jt} + \beta_1 \Delta\hat{\nu}_{ict} + \beta_3 \Delta \ln \frac{E_{ict}}{L_{ct}} + \beta_2 \Delta \ln L_{ct} + \Delta\epsilon_{ict} + \beta_1(\nu_{ict} - \hat{\nu}_{ict}) - \beta_1(\nu_{ict-1} - \hat{\nu}_{ict-1})) \\ &= d_{jt} + \beta_1 \Delta\hat{\nu}_{ict} + \beta_3 \Delta \ln \frac{E_{ict}}{L_{ct}} + \beta_2 \Delta \ln L_{ct} + \Delta\epsilon_{ict} + \beta_1(\xi_{ict} - \xi_{ict-1})\end{aligned}$$

D2. Implementation

Writing, $\nu_{ict} = \bar{\ln} w_{ict} - \alpha\bar{x}_{ict}$ and $\hat{\nu}_{ict} = \bar{\ln} w_{ict} - \hat{\alpha}\bar{x}_{ict}$ (where, $\bar{\ln} w_{ict}$ is the mean log wage within an i,c,t cell and $\bar{x}_{ict}$ is the vector of mean values of the covariates within the cell), we get:

$$\xi_{ict} = (\alpha - \hat{\alpha})\bar{x}_{ict}$$

We make two independence assumptions. First, we assume that the errors in the first-step individual wage equation are independent of the local productivity changes that are in the ϵ component of the error term in the main estimating equation . The second is that errors in individual wage equations are not correlated over time. Under these assumptions, this correction provides the appropriate asymptotic standard errors (Murphy and Topel, 1985, Theorem 1).

Given these assumptions, we arrive at our feasible estimator of the asymptotically correct standard error:

$$\hat{V}_{\Delta\epsilon} + \hat{\beta}_1^2 \cdot (\hat{\mathbf{Z}}'\hat{\mathbf{Z}})^{-1}\hat{\mathbf{Z}}' \left(\hat{V}_t + \hat{V}_{t-1}\right) \hat{\mathbf{Z}}(\hat{\mathbf{Z}}'\hat{\mathbf{Z}})^{-1}$$

where $\hat{V}_{\Delta\epsilon}$ is the standard (OLS or IV) cluster-robust variance-covariance matrix, that does not account for the two-step nature of our estimation procedure. As in Murphy and Topel (1985), this estimated variance-covariance matrix must be adjusted to account for sampling variation in the first-step estimation. The size of the correction will depend on the magnitude of the wage elasticity (captured by $\hat{\beta}_1$) and the relative error variance in the first-step. The correction is a function of $\hat{\mathbf{Z}}$, the $k \times (C \times I \times T - 1)$ matrix of regressors in the second-step, where k is the number of regressors, and C, I, and T are the number of cities, industries, and years in data set, respectively, and the matrices $\hat{V}_t$ and $\hat{V}_{t-1}$. The latter are calculated from the first-step estimates and have time subscripts because our second-step generated regressor is time-differenced. These matrices are computed as:

$$\hat{V}_t = \hat{\mathbf{X}}_t \hat{V}_{e_t} \hat{\mathbf{X}}_t'$$
$$\hat{V}_{t-1} = \hat{\mathbf{X}}_{t-1} \hat{V}_{e_{t-1}} \hat{\mathbf{X}}_{t-1}'$$

where $\hat{\mathbf{X}}_t$ is a $m \times (C \times I \times T - 1)$ matrix of the city-industry-year average of the explanatory variables appearing first-step estimation, and $\hat{V}_{e_t}$ is the first-step, cluster-robust, variance-covariance matrix.

Finally, note that our instruments are also functions of the generated, composition adjusted mean wages but, as is common in this situation, generated variables used in the construction of instruments does not alter the variance-covariance matrix associated with the IV estimates.

National level search by Entrepreneurs

The object of this section is to provide a more complete illustration of how random search by nationally mobile entrepreneurs can give rise to a specification of active entrepreneurship at the city industry level of the form $N^a_{ic} = \gamma_{0i} G(f^*) L_c^{\gamma_1}$, where the number of potential entrepreneurs in ic is given by $N_{ic} = \gamma_{0i} L_c^{\gamma_1}$. To this end, consider a continuous time environment where unattached entrepreneurs search across market (as specified by a industry and a city) in order to choose where to start a business. Entrepreneurs specialize in different industries. When an entrepreneur looking in industry i samples city c she learns the local wage and labor market tightness for that city, and hence learns the profitability of running a firm in this industry-city cell, which we can denote by π_{ic}. If the entrepreneur decides to start a business in city c, she must pay a fixed cost f that is drawn for the CDF $G(f)$. When searching in industry i, an entrepreneur faces a flow cost τ_i. Let the value of being an unattached entrepreneur searching in industry i be given by V_i^u, and let V^a_{ic} represent the value of being an active entrepreneur and running a business in industry i in city c. These value functions will will satisfy the following Bellman equations.

$$\rho V_i^u = -\tau_i + \sum_c \psi_{ic} E[\max[V^a_{ic} - \tilde{f}, V_i^u]$$

and

$$\rho V^a_{ic} = \pi_{ic} + \delta[V_i^u - V^a_{ic}]$$

where ρ is the entrepreneur's discount rate, ψ_c is instantaneous probability of sampling city c, $E[\cdot]$ is the expectation operator where the expectation is taken over the fixed cost f, and δ is the instantaneous probability of a firm closure.

Let us denote the total number of entrepreneurs (both unattached and active) in industry i by N_i, and let us assume that entry into entrepreneurship forces $V_i^u = 0$. From the Bellman equations, we can then infer that the cutoff entry cost in industry-city cell ic will be given by $f^*_{ic} = V^a_{ic}$ with $V^a_{ic} = \frac{\pi_{ic}}{\delta+\rho}$. The flow equation for each market will then need to satisfy

$$\delta N^a_{ic} = \psi_{ic} G(\frac{\pi_{ic}}{\delta+\rho})(N_i - \sum_{c'} N_{ic'}).$$

This implies that

$$N^a_{ic} = \psi_i c G(\frac{\pi_{ic}}{\delta+\rho})(1 - \frac{\sum_{c'} \psi_{ic} G(\frac{\pi_{ic}}{\delta+\rho})}{\delta + \sum_{c'} \psi_{ic} G(\frac{\pi_{ic}}{\delta+\rho}})N_i,$$

which is of the form

$$N^a_{ic} = \psi_{ic} G(f^*)\gamma_i.$$

If we further assume that the match rate ψ_{ic} is proportional to local population L_c, then we get precisely the desired relationship

$$N^a_{ic} = \gamma_{0i} G(f^*) L_c^{\gamma_1},$$

where $\gamma_{oi} L_c^{\gamma_1}$ corresponds to the potential entrepreneurs in industry i city c.

Alternative Estimates

F1. Alternative Estimates by Trade Groups

In this subsection, we present the table of results for industries grouped by tradeable status without imposing the restriction that the population coefficient be equal to 1. The implications for the short and longer run wage cost elasticities are very similar to those when the coefficient is restricted to 1, as reported in the main text of the paper.

F2. Breakdown by Education groups

The model we developed in section I conceptually applies to workers of a single skill group. In section II.A we discussed how we address worker heterogeneity in our baseline results by adjusting wages in accord with treating individuals as bundles of efficiency units. In this section, we report results from estimating our labor demand curve separately by education group. The education groups we consider are those with high school education or less and those with some post secondary or more.[11] When we perform this exercise, we are assuming that there are two completely segregated markets defined by education.[12] The

[11]We have assessed the sensitivity of our results to finer breakdowns in education which typically resulted in very imprecise estimates. Finer skill definitions dramatically reduce the number of city-industry cells to work with, resulting in sample size problems.

[12]Empirical evidence suggests that workers within our education classes are perfect substitutes, but that there is imperfect substitution of workers between the high- and low-education groups (Card, 2009). The latter type of substitution is ruled out in this framework.

Table F1—Estimates of Labor Demand Equation (6) by Trade Groups

	Low Trade		Medium Trade		High Trade	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \log w_{ict}$	0.13*	-0.73	0.11*	-0.79*	0.18*	-0.79*
	(0.028)	(0.47)	(0.020)	(0.30)	(0.027)	(0.23)
$\Delta \log \frac{E_{ct}}{L_{ct}}$	0.51*	-1.96	0.78*	-1.65*	0.89*	-1.33*
	(0.13)	(1.36)	(0.068)	(0.84)	(0.065)	(0.66)
$\Delta \log L_{ct}$	0.82*	0.87*	0.84*	0.86*	0.94*	0.95*
	(0.036)	(0.15)	(0.017)	(0.098)	(0.014)	(0.082)
Observations	5230	5220	14078	13929	14676	14399
R^2	0.62		0.60		0.56	
Instrument Set		Z_1, Z_2, Z_3, Z_4		Z_1, Z_2, Z_3, Z_4		Z_1, Z_2, Z_3, Z_4
F-Stats:						
$\Delta \log w_{ict}$		16.59		21.79		34.83
$\Delta \log \frac{E_{ct}}{L_{ct}}$		3.74		6.33		8.63
$\Delta \log P_{ct}$		35.60		43.09		36.76
AP p-val:						
$\Delta \log w_{ict}$		0.00		0.00		0.00
$\Delta \log \frac{E_{ct}}{L_{ct}}$		0.01		0.00		0.00
$\Delta \log P_{ct}$		0.00		0.00		0.00
Over-id. p-val		0.33		0.95		0.84

Notes: Standard errors, in parentheses, are clustered at the city-year level. (*) denotes significance at the 5% level. All models estimated on a sample of 152 U.S cities using Census and ACS data for 1970-2007. The dependent variable is the decadal change in log industry-city employment.

dependent variable in Table F2 is the change in log city-industry employment rate for a particular education group. Similarly, wages and their instruments are constructed separately by education group.[13] Columns 1-4 pertain to the low-education group and columns 5-8 to the high-education group. Inspection of the table reveals that the results for the high school educated group are very similar to those for the full sample. The results for the (smaller) college or more group are more erratic but tend to imply a similar sized wage elasticity.

Table F2—Estimates of Labour Demand Equation (6) By Education Group

	High School or Less				College or More			
	OLS	IV			OLS	IV		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta \log w_{ict}$	0.056*	-0.80	-0.91*	-0.87*	0.12*	-0.68	-1.37*	-1.39*
	(0.015)	(0.43)	(0.33)	(0.30)	(0.020)	(1.45)	(0.34)	(0.36)
$\Delta \log \frac{E_{ct}}{L_{ct}}$	0.84*	-1.94	-1.80*	-1.86*	0.69*	-7.73	-3.27	-3.60
	(0.045)	(1.06)	(0.84)	(0.88)	(0.11)	(9.80)	(1.95)	(2.14)
Observations	24717	24717	24717	24717	11768	11768	11768	11768
R^2	0.48				0.50			
Instruments		Z_1, Z_2	Z_1, Z_3	Z_1, Z_2, Z_3		Z_1, Z_2	Z_1, Z_3	Z_1, Z_2, Z_3
F-Stats:								
$\Delta \log w_{ict}$		19.26	22.60	23.25		6.91	23.94	16.18
$\Delta \log \frac{E_{ct}}{L_{ct}}$		4.75	8.65	5.78		1.68	5.25	3.69
$\Delta \log L_{ct}$								
AP p-val:								
$\Delta \log w_{ict}$		0.00	0.00	0.00		0.02	0.00	0.00
$\Delta \log \frac{E_{ct}}{L_{ct}}$		0.00	0.00	0.00		0.31	0.00	0.01
$\Delta \log L_{ct}$								
Over-id. p-val		.	.	0.82		.	.	0.51

Notes: Standard errors, in parentheses, are clustered at the city-year level. (*) denotes significance at the 5% level. All models estimat on a sample of 152 U.S cities using Census and ACS data for 1970-2007. The dependent variable is the decadal change in log industry-c employment rates.

In our second main robustness check, we allow for lagged wage effects. In the derivation of our labor demand specification, we downplayed potential dynamic effects arising from adjustment costs as our goal was to derive a labor demand specification appropriate for long-differences aimed at capturing the main, low frequency determinants of employment. In this exercise we briefly explore whether

[13]For example, Z_{2ct} and Z_{3ct} are constructed using city-industry shares and national wage premia that are estimated with education specific samples.

this approach could generate biased estimates due to the presence of dynamic effects that extend over periods of more than 10 years. In particular, in our theoretical framework we did not allow for existing firms to move across localities in search of low-wage areas. Firms, for example, may have gradually adjusted from the higher wage Northeastern labor market to the lower wage south and west. If this type of adjustment is present and it operates at low frequencies then this could bias our results. To explore this possibility, we re-estimate our labor demand equation allowing for the initial level of wages to affect the change in employment. The rationale for this extension is that the initial wage should capture incentives for entrepreneurs to move to low-wage cities. Since our measure of initial wages is likely affected by measurement error, we will also treat the initial wage level as an endogenous variable and add to our instrument set the level of wages ten years prior. It turns out that this instrument is an extremely strong predictor of initial wage levels as suggested by the F-statistics reported in Table F3.[14] Based on our earlier results, we use the employment rate as our dependent variable or, in other words, we constrain the coefficient on population growth to be 1. The first column of the table reports OLS estimates. Columns 2, 3 and 4 provide three different combinations for the instrument set.

Two observations emerge from these results. First, the estimate of the wage elasticity of employment at the city level remains close to -1. Second, there is very little evidence suggesting that initial wage levels play an important part in determining subsequent changes in employment. Although this does not imply that other types of dynamic effects are not present, it does provide some support for the claim that our rather static specification of labor demand may be appropriate for studying changes in employment over decades.

*

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[14]One drawback of using this additional instrument is that it forces us to drop the data for the 1970s.

Table F3—Estimates of Labor Demand, Allowing for Dynamics

	OLS	IV		
	(1)	(2)	(3)	(4)
$\Delta \log w_{ict}$	0.098*	-1.23*	-1.12	-1.03*
	(0.016)	(0.54)	(0.60)	(0.46)
$\Delta \log \frac{E_{ct}}{L_{ct}}$	0.79*	-4.00	-5.82	-4.26
	(0.048)	(3.38)	(5.27)	(3.37)
w_{ict-1}	-0.070*	0.0014	0.020	-0.0059
	(0.014)	(0.13)	(0.17)	(0.13)
Observations	33984	27673	27673	27673
R^2	0.51			
Instrument Set		Z_1, Z_2, w_{ict-2}	Z_1, Z_3, w_{ict-2}	Z_1, Z_2, Z_3, w_{ict-2}
F-Stats:				
$\Delta \log w_{ict}$		11.14	29.17	22.54
$\Delta \log \frac{E_{ct}}{L_{ct}}$		1.58	1.50	1.64
w_{ict-1}		178.28	158.87	138.77
AP p-val:				
$\Delta \log w_{ict}$		0.00	0.00	0.00
$\Delta \log \frac{E_{ct}}{L_{ct}}$		0.09	0.15	0.22
w_{ict-1}				
Over-id. p-val		.	.	0.54

Notes: Standard errors, in parentheses, are clustered at the city-year level. (*) denotes significance at the 5% level. All models estimated on a sample of 152 U.S cities using Census and ACS data for 1970-2007. The dependent variable is the decadal change in log industry-city employment rates.

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