The Incidence and Wage Consequences of Home-Based Work in the United States, 1980–2000

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ABSTRACT

This study documents the rapid growth in home-based wage and salary employment and the sharp decline in the home-based wage penalty in the United States between 1980 and 2000. These twin patterns, observed for both men and women in most occupation groups, suggest that employer costs of providing home-based work arrangements have decreased. Consistent with information technology (IT) advances being an important source of these falling costs, I find that occupation-gender cells that had larger increases in on-the-job IT use also experienced larger increases in the home-based employment share and larger declines in the home-based wage penalty.

I. Introduction

Home-based employment has grown at a rapid rate in the United States in recent decades. According to U.S. census data, the number of home-based workers nearly doubled between 1980 and 2000, growing from less than 2.2 million to nearly 4.2 million, while total employment grew at a much slower pace, from 96.6 million to 128.3 million.[1] Several forces operating over this time period potentially can explain this dramatic growth in home-based employment. First, the employment share of women grew substantially over this period, and women may value home-based work arrangements more highly than men given the traditional division

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1. The 1980 numbers can be found at http://www.census.gov/population/www/socdemo/workathome.html on the Census web site. The 2000 numbers can be found through the American FactFinder search tool on the Census web site.

of home production tasks within the family. Second, major advances in information and communications technology, which may have reduced the costs of providing home-based work arrangements, also occurred during these years. Finally, shifts in the occupational mix of the U.S. labor force over this period may have favored growth in home-based work.

The few existing empirical studies of home-based employment (Kraut and Grambsch 1987; Kraut 1988; Presser and Bamberger 1993; Edwards and Field-Hendry 2001, 2002; Pabilonia 2005; Schroeder and Warren 2005) all have analyzed its determinants or wage consequences at a point in time. While valuable, these studies offer little insight into why home-based employment has expanded so rapidly in recent years. The present paper begins to fill this gap by using data from the Public Use Micro Samples (PUMS) of the 1980, 1990, and 2000 U.S. Censuses to analyze in detail both the recent growth in home-based wage and salary employment and the contemporaneous changes in the wages of home-based employees relative to onsite workers.

I find that the rapid growth in home-based wage and salary employment was accompanied by a dramatic decline in the wage penalty associated with home-based work, from roughly 30 log points in 1980 to approximately zero in 2000. More disaggregated analyses reveal that home-based employment shares rose and home-based wage penalties declined in almost all occupation categories, for both men and women, and that only small fractions of the growth in the overall home-based employment share and the decline in the average home-based wage penalty can be explained by compositional shifts favoring occupation groups with high propensities toward and low-wage penalties from home-based work. These results suggest that broad-based reductions in employer costs of providing home-based work arrangements have been the predominant force behind the growth in home-based employment since 1980.

I then investigate whether the data are consistent with advances in information technology (IT) being a major source of these decreasing costs. If IT advances played an important role, gender-occupation categories that saw greater growth in on-the-job IT use should have experienced larger increases in home-based employment shares and larger declines in home-based wage penalties. I use data from Current Population Survey (CPS) supplements to construct measures of IT use within gender $\times$ occupation $\times$ year cells and find evidence consistent with these hypotheses. I also use data from the Occupational Information Network (O*NET)—the database that replaced the Dictionary of Occupational Titles (DOT)—to compute, for each gender-occupation category, the fraction of jobs requiring less than weekly face-to-face discussion with customers or coworkers. I find some evidence that, for a given level of growth in on-the-job IT use, home-based employment shares grew more in gender-occupation cells with a higher fraction of jobs requiring less than weekly face-to-face discussion. However, I find no evidence that an analogous interaction effect helps account for the pattern of decline in home-based wage penalties.

The remainder of the paper unfolds as follows. Section II discusses the census data and summarizes the recent growth in home-based employment in the United States in more detail. Section III gives a brief theoretical discussion of the possible wage consequences of the growth in home-based employment and then describes the empirical analyses to be undertaken. Section IV presents the results of the empirical analyses and Section V concludes.

II. Data

The empirical analyses use data from the 5 percent Public Use Microdata Samples (PUMS) of the U.S. Census of Population for 1980, 1990, and 2000. In each of these years, the census long form contained a question about the method of transportation used to get to work on the most days in the previous week. Responses to this question were obtained for all individuals who were aged 16 or older and were employed in the previous week. I classify employed individuals who select the response "worked at home" as home-based workers and classify all others as onsite workers. Since only individuals who *mainly* work at home are counted as home-based, the frequency of home-based employment in the census data is a conservative lower bound on the fraction of workers who do *any* work at home.[2]

For each census year, I construct analysis samples by first selecting all households that contain one or more home-based workers and a random 1 percent sample of households that contain zero home-based workers.[3] From this set of households I keep all individuals aged 25–64 who were employed in paid civilian jobs in the previous week. In addition, as is discussed further below, I drop the self-employed and limit attention to wage and salary workers in most of the analyses. Thus, the study primarily focuses on prime-age, civilian, wage-and-salary workers.

For all analyses of wages, I compute the hourly wage as wage and salary income in the previous calendar year divided by the product of weeks worked in the previous calendar year and usual hours worked per week. Reported wage and salary income was topcoded at $75,000, $140,000, and $175,000 in the 1980, 1990, and 2000 censuses, respectively.[4] For observations with topcoded wage and salary income, I impute annual wage and salary income as 1.5 times the topcode income level before computing the hourly wage. I convert the nominal hourly wage in all census years to real 1999 dollars using the CPI for all urban consumers. Because reported wage and salary income corresponds to the previous calendar year, some or all of this income may have been earned on a different job than the one held on the census date (April 1), from which home-based work status is determined. Thus, home-based work status (and other job characteristics) may be measured with some error with respect to the wage calculated from prior year earnings. This potential misclassification of home-based work status could cause bias in cross-section estimates, but it will affect over time comparisons only if the durability of home-based jobs has

2. In fact, data from the May 2001 Current Population Survey indicate that 19.8 million workers did *some* work at home at least once a week. This number is taken from the U.S. Bureau of Labor Statistics news release "Work at Home in 2001" available at http://www.bls.gov/news.release/homey.nr0.htm.
3. I adjust the census-provided sample weights to account for the differential probabilities of sample inclusion for individuals from households with home-based workers and individuals from households without home-based workers and I use these adjusted weights in all of the empirical analyses.
4. In real dollars, the topcode income levels in all three census years are very similar.

Table 1
Employment Levels, Home-Based Employment Shares, and Their Growth Rates, for Paid Civilian Workers Aged 25–64, by Employment Type and Year

	Employment (In 000's) or Home-Based Share			Percentage Growth		
Employment Type	1980	1990	2000	1980–1990	1990–2000	1980–2000
All employment	71,598	91,943	104,218	28.6	13.4	45.7
On site	69,935	89,351	100,808	27.8	12.8	44.1
Home-based	1,584	2,592	3,420	63.6	31.6	115.3
Home-based share	0.0221	0.0282	0.0327	27.6	16.0	48.0
Wage and salary	64,098	82,428	93,185	28.6	13.1	45.4
Onsite	63,618	81,623	91,840	28.3	12.5	44.4
Home-based	480	805	1,345	67.6	67.2	180.2
Home-based share	0.0075	0.0098	0.0144	30.3	47.9	92.7
Self-employment	7,421	9,515	11,033	28.2	16.0	48.7
Onsite	6,317	7,728	8,968	22.3	16.0	42.0
Home-based	1,104	1,787	2,065	61.9	15.6	87.1
Home-based share	0.1487	0.1878	0.1872	26.3	−0.3	25.9

Note: Data come from the 5 percent PUMS of the U.S. Census of Population for 1980, 1990, and 2000. The samples consist of individuals aged 25–64 who worked for pay in civilian jobs in the week prior to the census. The samples include all such individuals from households containing at least one home-based worker and all such individuals from a 1 percent random sample of households containing no home-based workers. The results in this and all other tables use the census sample weights, adjusted for the differential probabilities of sample inclusion for individuals from households with and without any home-based workers. Self-employment includes self-employed individuals working in both incorporated and unincorporated businesses.

changed substantially over time. However, the available evidence for all jobs does not indicate any large secular trend in job stability.[5]

Table 1 documents the rapid growth in home-based employment among paid civilian workers aged 25–64. The top panel of the table shows that employment of all home-based workers more than doubled between 1980 and 2000 (from 1.58 million to 3.42 million) while employment of all onsite workers grew by only 44.1 percent (from almost 70 million to around 100.8 million) over the same period.[6] The remaining panels highlight the substantial differences in both the level and the growth of home-based employment between wage and salary employees and the

5. For evidence, see Farber (1999), Jaeger and Stevens (1999), and Neumark, Polsky, and Hansen (1999).
6. This growth rate of home-based employment among paid civilian workers aged 25–64 is higher than that for all workers cited in the introduction. Evidently, home-based work grew faster among prime-age civilian workers than it did among the young, the elderly, and military employees between 1980 and 2000.

self-employed. Home-based employment has been very uncommon among wage and salary workers but has grown extremely rapidly in recent decades, dwarfing the growth rate of onsite wage and salary employment. In contrast, home-based self-employment has been much more common but has grown at a considerably slower rate in recent decades.

For several reasons, I restrict attention to home-based wage and salary workers in the rest of the paper. First, the different growth trends for home-based wage and salary employment and home-based self-employment suggests that different forces may have driven the growth in these two employment sectors, which in turn suggests that the two sectors should be analyzed separately. Furthermore, within the conceptual framework presented below, an analysis of changes in the relative wages of home-based workers can shed light on the causes of growth in home-based work. This framework assumes that (i) each worker faces a parametric market wage given her skills, (ii) observed average hourly earnings are a good proxy for this (constant) marginal wage, and (iii) there exists a market compensating differential for the non-wage job attribute "home-basedness." These assumptions seem reasonable for wage and salary workers but not for the self-employed. By dropping the self-employed I avoid these difficulties, albeit at the cost of ignoring a quantitatively important component of total home-based employment.

III. Theoretical Considerations and Empirical Strategy

"Home-basedness" is a job attribute that is worth more to workers with high opportunity costs of spending time away from home and that is less costly to provide on jobs where in-person interaction with coworkers, supervisors, or physically immobile capital inputs is not required. In equilibrium, a market compensating differential for "home-basedness" will equalize the number of workers seeking home-based jobs and the number of home-based jobs offered by employers, and will match workers who value this attribute most with employers who can provide it at lowest cost.[7] A wage penalty for home-based work will exist in equilibrium if and only if "home-basedness" is valuable to the marginal home-based worker and is costly to provide for the marginal employer offering home-based work.[8]

The growth over time in the home-based share of wage and salary employment could be explained either by rising worker valuations for such work arrangements (an outward shift in the relative supply of labor to home-based jobs) or by falling employer costs of offering them (an outward shift in the relative demand for labor in home-based jobs). Rising female labor force participation or changes in preferences or income within demographic groups may have increased worker valuations

7. Rosen (1986) surveys the theory of compensating differentials in detail. A large empirical literature attempts to measure compensating differentials for various job attributes including fatality risk (Thaler and Rosen 1975), unemployment risk (Abowd and Ashenfelter 1981; Topel 1984), shift work (Kostiuk 1990), and employer-provided health insurance benefits (Olson 2002).

8. "Home-basedness" may have negative value for some workers (for example, those who enjoy socializing at work) and may lower costs for some employers (for example, those that can reduce the amount of rented office space).

of home-based work in recent decades. Over this same period, IT advances may have reduced employers' nonwage costs of providing home-based work arrangements. Fortunately, the observed change in the home-based wage penalty (or premium) over this time period can provide evidence on the relative importance of these competing explanations. In particular, if rising worker valuations for home-based work were the dominant factor, the home-based wage penalty should have increased in recent decades. In contrast, if decreasing employer costs of offering home-based jobs were the major driving force, the home-based wage penalty should have fallen over time.

To provide initial evidence on whether the growth in home-based employment is mainly due to rising worker valuations for such work arrangements or falling employer costs of providing them, I estimate log wage regressions of the form

$$\ln W_{ist} = X_{ist}\beta_{st} + \delta_{st}H_{ist} + \varepsilon_{ist}, \tag{1}$$

where i indexes individuals, s indexes gender, t indexes census year, X is a vector of human capital variables, and H is a dummy for home-based employment status. This specification allows the penalty for home-based work (and the returns to observed human capital) to vary by gender and year, and the question of interest is how the estimated (male and female) home-based wage penalties, $\hat{\delta}_{st}$, have changed over time.

The empirical specification in Equation 1 estimates a common home-based wage penalty for all occupations within each gender-year sample. This restriction is unpalatable if, as seems likely, home-based work arrangements can be provided at much lower cost for some jobs than for others. Moreover, if such cost heterogeneity exists, any changes in the aggregate home-based penalty estimated by Equation 1 will confound the effects of shifts in the occupational composition of home-based employment with changes in home-based wage penalties within occupations. Similarly, shifts in the occupational composition of the overall labor force might explain some of the growth in home-based employment documented earlier. To address these questions, I next estimate models of the form

$$\ln W_{ist} = X_{ist}\beta_{st} + \sum_{j=1}^{20}\delta_{jst}D^{j}_{ist}H_{ist} + \varepsilon_{ist}, \tag{2}$$

where D^{j}_{ist} is a dummy that equals 1 if the sample individual is employed in occupation category j and the other variables are defined as in Equation 1.[9] This specification estimates 20 occupation-specific home-based wage penalties in each gender-year sample and allows Oaxaca-type decompositions to be used to assess the role of compositional shifts in explaining changes in the aggregate home-based wage penalty. Analogously, I tabulate home-based employment shares for each of the 20 occupation groups in each gender-year sample and use decomposition methods to evaluate the extent to which compositional shifts explain changes in the aggregate home-based employment share.

9. The complete vector of occupation dummies, D, which captures the main effects of occupational affiliation on wages, is a component of the human capital vector, X, in Equations 1 and 2.

Finally, I examine whether the variation in home-based employment shares and home-based wage penalties across gender $\times$ occupation $\times$ year cells can be partly explained by across-cell variation in on-the-job IT use and whether this relationship is moderated by how frequently face-to-face discussion with coworkers or customers is required on the job. This analysis is motivated by the observation that home-based employment shares (wage penalties) should have increased (decreased) more in gender-occupation cells where on-the-job IT use grew more—*if* this greater utilization of IT substantially lowered employer costs of offering home-based jobs. To test this hypothesis, I estimate variants of the model

$$(3) \quad y_{jst} = \gamma_1 IT_{jst} + \gamma_2 (IT_{jst} \times LessThanWeeklyDiscussion_{js}) + \phi_{js} + \theta_t + u_{jst},$$

where j indexes occupation group, s indexes gender, t indexes census year, y_{jst} is either the cell-specific home-based employment share or cell-specific home-based wage penalty, IT_{jst} is a gender $\times$ occupation $\times$ year-specific rate of on-the-job IT use[10], and $LessThanWeeklyDiscussion_{js}$ is the fraction of jobs in each gender $\times$ occupation cell that require less than weekly face-to-face discussion with coworkers or customers.[11]

If more IT-intensive jobs can be performed from home more cheaply, then higher on-the-job IT use should be associated with higher (lower) home-based employment shares (wage penalties) and I should find $\hat{\gamma}_1 > 0$. If this effect is stronger for jobs that require less face-to-face interaction, then I also should find $\hat{\gamma}_2 > 0$. Note that I look for these relationships of interest after controlling for both fixed gender-occupation effects and fixed time effects, factors that almost certainly account for much of the variation in home-based employment shares and home-based wage penalties.

IV. Empirical Analyses

A. Descriptive Statistics

Before reporting estimates of the wage penalty on home-based jobs, Tables 2A and 2B present, for males and females respectively, descriptive statistics on the wages and human capital attributes of onsite and home-based workers between 1980 and 2000. The samples of wage and salary workers are the same as in Table 1, but with the added restriction that only observations with real hourly wages between \$1 and \$150 are included. The relative wage gains made by home-based workers over these 20 years are striking. In 1980, the mean log real wage of home-based workers was far below that of onsite workers, for both men and women. By 2000, however,

10. This variable is computed using micro data on civilian wage and salary workers aged 25–64 from special CPS supplements in October 1984, September 1993, and September 2001. Details on how this variable is constructed are provided in Section IV below.

11. This variable is computed using a single cross-section of data from O*NET on the fraction of jobs requiring less than weekly face-to-face discussion with coworkers or customers in each of over 500 highly detailed occupations. I compute fractions for my gender-occupation cells by taking gender-specific employment weighted averages over all individual occupations in each cell. Details on how this variable is constructed are provided in section IV below.

Table 2A
Sample Means (Standard Deviations) for Key Variables for Male Wage and Salary Workers Aged 25–64, by Year and Onsite/Home-Based Status

	1980		1990		2000	
	Onsite	Home-Based	Onsite	Home-Based	Onsite	Home-Based
Log of real hourly wage	2.87	2.49	2.79	2.59	2.77	2.91
(in 1999 $)	(0.60)	(0.85)	(0.60)	(0.81)	(0.61)	(0.75)
Part-time worker	0.042	0.103	0.048	0.112	0.051	0.085
Part-year worker	0.147	0.190	0.144	0.189	0.124	0.125
Disabled	0.048	0.083	0.038	0.069	0.109	0.094
Less than high school	0.227	0.237	0.125	0.125	0.099	0.059
High school degree	0.343	0.276	0.321	0.239	0.306	0.177
Some college	0.184	0.163	0.288	0.252	0.292	0.265
College degree or more	0.246	0.324	0.266	0.384	0.303	0.499
Managerial, business	0.143	0.196	0.144	0.187	0.140	0.238
Engineers, scientists	0.050	0.023	0.052	0.035	0.062	0.082
Healthcare practitioners	0.011	0.005	0.014	0.005	0.014	0.007
Teachers, educators	0.041	0.024	0.036	0.024	0.032	0.017
Arts, media, social service	0.018	0.124	0.026	0.132	0.029	0.076
Lawyers, judges	0.006	0.005	0.006	0.002	0.007	0.004
Technicians	0.035	0.017	0.043	0.023	0.042	0.046
Sales supervisors & reps	0.055	0.106	0.069	0.144	0.056	0.145
Retail sales workers	0.023	0.023	0.025	0.032	0.034	0.072
Office support workers	0.030	0.017	0.023	0.016	0.034	0.031
Mail & shipping clerks	0.049	0.026	0.052	0.024	0.045	0.028
Protective service	0.028	0.011	0.031	0.011	0.035	0.013
Food or cleaning service	0.043	0.057	0.049	0.056	0.059	0.036
Health or personal service	0.007	0.016	0.009	0.016	0.011	0.021
Farming, forestry, fishing	0.016	0.159	0.019	0.112	0.010	0.027
Mechanics & repairers	0.067	0.026	0.067	0.036	0.073	0.037
Construction trades	0.065	0.038	0.069	0.032	0.095	0.038
Extractive, precision production	0.077	0.024	0.059	0.018	0.049	0.016
Machine operators	0.109	0.033	0.084	0.027	0.080	0.027
Vehicle operators	0.126	0.070	0.124	0.069	0.094	0.037
Observations (unweighted)	37,612	9,140	65,540	16,560	74,911	28,665

Note: See the note to Table 1 for a description of the data source and sample construction. The sample is limited to individuals with real hourly wages between $1 and $150. The descriptive statistics are weighted to adjust for differential probabilities of sampling across individuals and are therefore representative of the population aged 25–64 in paid civilian employment in the week prior to the census. Part-time work is defined as usually working less than 35 hours per week and part-year work is defined as working less than 48 weeks in the previous calendar year.

Table 2B
Sample Means (Standard Deviations) for Key Variables for Female Wage and Salary Workers Aged 25–64, by Year and Onsite/Home-Based Status

	1980		1990		2000	
	Onsite	Home-Based	Onsite	Home-Based	Onsite	Home-Based
Log of real hourly wage	2.42	2.08	2.47	2.25	2.55	2.53
(in 1999 dollars)	(0.58)	(0.84)	(0.59)	(0.75)	(0.60)	(0.76)
Part-time worker	0.228	0.471	0.214	0.438	0.190	0.340
Part-year worker	0.315	0.386	0.250	0.315	0.217	0.232
Disabled	0.030	0.071	0.031	0.060	0.099	0.094
Less than high school	0.195	0.216	0.090	0.126	0.066	0.069
High school degree	0.428	0.407	0.349	0.330	0.291	0.244
Some college	0.185	0.200	0.309	0.293	0.332	0.326
College degree or more	0.192	0.177	0.252	0.251	0.311	0.361
Managerial, business	0.085	0.130	0.129	0.158	0.131	0.183
Engineers, scientists	0.008	0.005	0.016	0.012	0.021	0.033
Healthcare practitioners	0.046	0.011	0.053	0.017	0.061	0.021
Teachers, educators	0.094	0.035	0.091	0.035	0.089	0.033
Arts, media, social service	0.021	0.040	0.025	0.056	0.038	0.063
Lawyers, judges	0.002	0.001	0.004	0.002	0.005	0.006
Technicians	0.032	0.014	0.042	0.016	0.047	0.033
Sales supervisors & reps	0.026	0.029	0.043	0.055	0.040	0.060
Retail sales workers	0.058	0.059	0.052	0.051	0.051	0.065
Office support workers	0.218	0.245	0.182	0.221	0.187	0.184
Mail & shipping clerks	0.102	0.048	0.104	0.061	0.093	0.067
Protective service	0.004	0.002	0.006	0.002	0.009	0.003
Food or cleaning service	0.085	0.079	0.075	0.087	0.072	0.036
Health or personal service	0.063	0.207	0.056	0.128	0.062	0.156
Farming, forestry, fishing	0.004	0.021	0.006	0.023	0.003	0.008
Mechanics & repairers	0.004	0.001	0.004	0.002	0.005	0.003
Construction trades	0.001	0.002	0.002	0.004	0.003	0.003
Extractive, precision production	0.018	0.014	0.017	0.016	0.012	0.008
Machine operators	0.100	0.043	0.065	0.041	0.050	0.026
Vehicle operators	0.030	0.013	0.027	0.014	0.021	0.009
Observations (unweighted)	26,426	12,159	46,966	21,120	61,370	34,518

Note: See the note to Table 2A.

female home-based workers had achieved wage parity with their onsite counterparts and male home-based workers had actually surpassed their onsite counterparts.

The relative wage gains made by home-based workers were accompanied by relative gains in labor force attachment and educational attainment. In 1980, home-based workers were much more likely than onsite workers to work on a part-time or part-year basis or to have a disability; by 2000, these gaps had diminished substantially and, in some cases, disappeared.[12] With respect to education, home-based workers and onsite workers had similar attainments in 1980, but home-based workers had an advantage by 2000 and, for males, the gap was quite large.

The final panels of Tables 2A and 2B report occupational distributions, by gender and home-based work status, between 1980 and 2000. Not surprisingly, the occupational distributions differ substantially between males and females (holding home-based work status constant) and between onsite and home-based workers (holding gender constant) in all years.[13] Perusal of the home-based worker occupational distributions reveals that home-based employment shifted from farming and (some) service jobs toward managerial, scientific, and sales jobs over the sample period.

B. Estimates of the Wage Penalty on Home-Based Jobs, 1980–2000

Clearly, one must adjust for the large differences in skills and labor force attachment between onsite and home-based workers when attempting to measure the home-based wage penalty in each gender-year sample. To this end, I report OLS estimates of Model 1 in Table 3.[14] I do not discuss the estimated coefficients on the covariates other than home-based work status, which generally have the expected signs and magnitudes.[15] Interestingly, the estimated male and female home-based wage penalties differ little in each census year after controlling for observable human capital. More importantly, both male and female home-based wage penalties have fallen

12. Reported *levels* of disability rose in 2000 for all workers, irrespective of home-based status or sex, because of a change in the wording of the census question about disability status. However, the *relative* frequency of disability among home-based workers declined sharply in 2000.

13. In unreported tabulations using the complete 5 percent sample from the 2000 census, I also find large gender differences in the detailed occupational distributions *within* the 20 occupational groups defined in Tables 2A and 2B. This evidence that men and women tend to work in different specific occupations within occupational categories provides support for estimating the empirical models separately by gender.

14. OLS estimates of δ_{st} will be consistent for the true market compensating differential for home-based employment only if the unobserved wage component is uncorrelated with home-based work status. If workers with high unobserved skills "buy" more desirable job attributes (as suggested by Brown 1980) and if working from home is desirable, the unobserved wage component and home-based work status will tend to be positively correlated. On the other hand, working from home eliminates fixed commuting costs (as emphasized by Edwards and Field-Hendry 2001, 2002), which is more likely to alter work decisions of low-wage workers and which therefore will tend to induce a negative correlation between the unobserved wage component and home-based work status. Thus, the sign of any bias in cross-section estimates of the home-based work compensating differential is unclear a priori. Still, changes over time in estimated home-based wage penalties may partly reflect changes in unobserved skills of home-based workers (relative to onsite workers) rather than pure changes in the implicit price of "home-basedness" for a worker of fixed skill. However, this potential confound is likely to be less severe in the analyses that estimate separate home-based wage penalties for each gender-occupation group.

15. One small anomaly is the decline in the estimated wage penalty associated with disability in 2000, but this is likely an artifact of the less-stringent definition of disability used in the 2000 census.

Table 3
Log wage regressions for wage and salary workers aged 25–64, separately by year and gender, allowing for a homogeneous wage penalty for home-based work

	Males			Females		
	1980	1990	2000	1980	1990	2000
Potential experience	0.036	0.034	0.025	0.018	0.020	0.022
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
(Potential experience squared)/100	−0.056	−0.05	−0.038	−0.032	−0.032	−0.036
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)
Less than high school degree	−0.145	−0.205	−0.162	−0.064	−0.084	−0.131
	(0.012)	(0.014)	(0.015)	(0.015)	(0.017)	(0.019)
Some college	0.074	0.105	0.122	0.073	0.114	0.129
	(0.012)	(0.010)	(0.010)	(0.013)	(0.011)	(0.010)
College degree or more	0.287	0.346	0.330	0.259	0.367	0.398
	(0.014)	(0.013)	(0.013)	(0.017)	(0.014)	(0.013)
Black	−0.131	−0.087	−0.060	0.062	0.022	0.007
	(0.016)	(0.015)	(0.014)	(0.016)	(0.015)	(0.013)
Hispanic	−0.110	−0.106	−0.109	0.004	−0.005	−0.046
	(0.018)	(0.015)	(0.014)	(0.022)	(0.021)	(0.016)
Married	0.099	0.119	0.136	−0.017	−0.021	0.001
	(0.012)	(0.010)	(0.010)	(0.010)	(0.009)	(0.008)
Number of kids	0.016	0.010	0.010	−0.036	−0.031	−0.017
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Disabled	−0.170	−0.147	−0.059	−0.117	−0.112	−0.034
	(0.022)	(0.022)	(0.013)	(0.031)	(0.029)	(0.014)
Home-based worker	−0.314	−0.180	0.015	−0.290	−0.170	−0.030
	(0.012)	(0.010)	(0.007)	(0.011)	(0.009)	(0.007)
R^2	0.224	0.296	0.281	0.198	0.267	0.281
Number of observations (unweighted)	46,752	82,100	103,576	38,585	68,086	95,888

Note: Heteroskedasticity-robust standard errors are shown in parentheses. The estimates use the adjusted census sample weights that account for the varying probability of sample inclusion across observations. All specifications also include dummies for seven industries, 19 occupations, part-time work status, and part-year work status.

dramatically over time, from about 30 log points in 1980 to essentially zero in 2000. This decrease in the home-based wage penalties over time is consistent with the idea that falling employer costs of providing home-based work arrangements were the main force driving the growth in home-based employment between 1980 and 2000. However, this trend in the mean home-based wage penalty also would be observed if home-based wage penalties vary across occupations and if home-based employment has shifted toward occupations with lower home-based wage penalties in recent decades. Moreover, since employers' costs of offering home-based work arrangements may vary with job tasks and since workers' valuations of working at home may vary with full income or personal attributes, it is in fact likely that both home-based employment shares and home-based wage penalties vary a lot across occupations. Thus, it is important to investigate whether such heterogeneity is present in the data.

C. Occupational Heterogeneity in Home-Based Employment Shares and Wage Penalties

Table 4 presents estimates of occupation-specific home-based employment shares and occupation-specific home-based wage penalties for all six gender-year samples using 20 mutually exclusive and exhaustive occupation categories. The hypothesis that the shares of home-based workers are equal across occupation groups can be rejected at conventional significance levels in all gender-year samples. In most occupation-year cells, women were more likely to hold home-based jobs than men, reflecting gender differences either in preferences or in detailed occupational affiliation within occupation categories. In nearly all gender-occupation cells, the home-based employment share grew between 1980 and 2000, although the pace of this growth varied substantially across cells.

Occupation-specific home-based wage penalties are obtained by estimating the log wage regression in Equation 2. To save space, the table reports point estimates only for the occupation × home-based work status interaction terms and does not report standard errors.[16] As was true for home-based employment shares, the hypothesis that the wage penalties on home-based jobs were identical across occupation categories is soundly rejected in every gender-year sample. Wage penalties for home-based employment shrank over time in the vast majority of gender-occupation categories; in 1980, these penalties were large in most categories but, by the year 2000, home-based workers in a few gender-occupation groups (for example, sales workers and engineers of both sexes) actually earned substantially more on average than observationally equivalent onsite workers.

Given that home-based employment shares (wage penalties) varied a lot across occupations, it is reasonable to ask whether shifts in the occupational composition of overall (home-based) employment can explain much of the increase (decrease) in the aggregate home-based employment share (wage penalty). To answer these questions, I use standard decomposition techniques. Let H_{st} denote the home-based employment share among all wage and salary workers aged 25–64 of gender s at date t. Let H_{jst} denote the analogous home-based employment share within occupation group j. Then $H_{st} = \sum_{j=1}^{20} f_{jst} H_{jst}$, where f_{jst} is occupation group j's share in total wage and salary employment of gender s at date t. The change in the average home-based employment share of gender s between dates t and τ can be decomposed as

$$(4) \quad H_{s\tau} - H_{st} = \sum_{j=1}^{20} (f_{js\tau} - f_{jst}) \left(\frac{H_{js\tau} + H_{jst}}{2} \right) + \sum_{j=1}^{20} \left(\frac{f_{js\tau} + f_{jst}}{2} \right) (H_{js\tau} - H_{jst}).$$

The first term in Equation 4 is the part of the change in the aggregate home-based share of gender s that is explained by changes over time in the occupational distri-

16. The point estimates on the other covariates are virtually identical to those reported in Table 3. The home-based wage penalties are mostly estimated with reasonable precision; the median standard error across all gender-occupation categories is 0.050 in 1980, 0.040 in 1990, and 0.028 in 2000.

Table 4
Actual home-based employment shares and estimated home-based wage penalties, by occupation-gender category and year

	Home-Based Employment Share			Home-Based Wage Penalty		
Occupation category	1980	1990	2000	1980	1990	2000
A. Males						
Managerial, business	0.0070	0.0098	0.0207	−0.3612	−0.2314	0.0027
Engineers, scientists	0.0023	0.0052	0.0160	−0.1569	−0.0775	0.1053
Healthcare practitioners	0.0021	0.0026	0.0060	−0.2354	0.0052	−0.0682
Teachers, educators	0.0030	0.0051	0.0067	−0.3323	−0.2341	−0.0780
Arts, media, social service	0.0343	0.0379	0.0315	−0.6621	−0.4589	−0.3301
Lawyers, judges	0.0037	0.0030	0.0081	−0.6575	−0.1490	−0.2083
Technicians	0.0024	0.0040	0.0136	−0.2043	−0.0284	0.0703
Sales supervisors & reps	0.0098	0.0157	0.0312	−0.0282	0.0497	0.1681
Retail sales	0.0051	0.0098	0.0258	0.0011	0.1051	0.2833
Office support	0.0030	0.0051	0.0111	−0.2708	−0.2387	0.1555
Mail & shipping clerks	0.0027	0.0035	0.0078	−0.1780	−0.1323	0.0908
Protective service	0.0020	0.0027	0.0045	−0.3881	−0.1873	−0.0016
Food or cleaning service	0.0068	0.0086	0.0075	−0.2736	−0.1805	−0.0774
Health or personal service	0.0112	0.0141	0.0241	−0.5076	−0.0804	−0.2127
Farming, forestry, fishing	0.0493	0.0438	0.0328	−0.3793	−0.2319	−0.0746
Mechanics & repairers	0.0020	0.0041	0.0062	−0.2347	−0.2827	−0.0952
Construction trades	0.0030	0.0036	0.0049	−0.1918	−0.1133	−0.1089
Extractive, precision production	0.0016	0.0023	0.0040	−0.2056	−0.1388	−0.0491
Machine operators	0.0016	0.0024	0.0042	−0.2231	−0.2481	−0.0702
Vehicle operators	0.0028	0.0042	0.0049	−0.2436	−0.1308	−0.0596
B. Females						
Managerial, business	0.0139	0.0132	0.0221	−0.4033	−0.2904	−0.0403
Engineers, scientists	0.0056	0.0076	0.0248	−0.3389	−0.1269	0.0960
Healthcare practitioners	0.0023	0.0034	0.0056	−0.3121	−0.3182	−0.0942
Teachers, educators	0.0035	0.0041	0.0060	−0.3444	−0.2944	−0.0802
Arts, media, social service	0.0170	0.0239	0.0258	−0.2927	−0.2195	−0.0565
Lawyers, judges	0.0065	0.0051	0.0165	−0.0518	−0.2413	0.1661
Technicians	0.0040	0.0042	0.0112	−0.2601	−0.0230	0.0387
Sales supervisors & reps	0.0104	0.0137	0.0234	−0.1378	0.0206	0.1373
Retail sales	0.0094	0.0104	0.0201	−0.0698	0.0140	0.2269
Office support	0.0103	0.0130	0.0156	−0.0711	−0.0568	−0.0217
Mail & shipping clerks	0.0043	0.0063	0.0116	−0.0518	−0.0734	0.0366

(continued)

Table 4 *(continued)*

	Home-Based Employment Share			Home-Based Wage Penalty		
Occupation category	1980	1990	2000	1980	1990	2000
Protective service	0.0049	0.0041	0.0062	−0.3321	0.0140	−0.0548
Food or cleaning service	0.0085	0.0124	0.0079	−0.2645	−0.2176	−0.0941
Health or personal service	0.0297	0.0243	0.0389	−0.6530	−0.3234	−0.2121
Farming, forestry, fishing	0.0512	0.0410	0.0397	−0.2318	−0.0678	−0.1578
Mechanics & repairers	0.0019	0.0055	0.0093	−0.2055	−0.2569	−0.0757
Construction trades	0.0132	0.0174	0.0132	−0.2533	−0.2885	−0.0145
Extractive, precision production	0.0072	0.0105	0.0108	−0.3185	−0.2664	−0.2286
Machine operators	0.0040	0.0068	0.0085	−0.2062	−0.1690	−0.0667
Vehicle operators	0.0040	0.0056	0.0073	−0.1729	−0.2490	−0.0122

Note: The wage penalties reported in the three right-hand columns are the estimated coefficients on interactions between the home-based indicator and the 20 occupation category dummies from regressions of the form of Equation 2 in the paper, estimated separately by gender and year. These regressions also include all of the explanatory variables listed in Table 3.

bution of employment, given the average occupation-specific propensities for home-based work at dates t and τ. The second term in Equation 4 is the part of the change in the aggregate home-based share of gender s that is explained by changes over time in the propensities for home-based work *within* occupation groups.

Turning to the home-based wage penalties, the empirical specification in Equation 2 and properties of least squares regression imply that the mean log wage can be written as $\overline{\ln W^O_{st}} = \overline{X^O_{st}}\hat{\beta}_{st}$ for onsite workers of gender s at time t and can be written as $\overline{\ln W^H_{st}} = \overline{X^H_{st}}\hat{\beta}_{st} + \sum_{j=1}^{20} \overline{D^j_{st}}\,\hat{\delta}_{jst}$ for home-based workers of gender s at time t. Some simple algebra yields the following expression for the change in the mean log wage difference between home-based and onsite workers of gender s between dates t and τ:

$$(5)\quad (\overline{\ln W^H_{s\tau}} - \overline{\ln W^O_{s\tau}}) - (\overline{\ln W^H_{st}} - \overline{\ln W^O_{st}}) = ((\overline{X^H_{s\tau}} - \overline{X^O_{s\tau}}) - (\overline{X^H_{st}} - \overline{X^O_{st}}))\left(\frac{\hat{\beta}_{s\tau} + \hat{\beta}_{st}}{2}\right)$$
$$+ \left(\left(\frac{\overline{X^H_{s\tau}} + \overline{X^H_{st}}}{2}\right) - \left(\frac{\overline{X^O_{s\tau}} + \overline{X^O_{st}}}{2}\right)\right)(\hat{\beta}_{s\tau} - \hat{\beta}_{st}) + \sum_{j=1}^{20}(\overline{D^j_{s\tau}} - \overline{D^j_{st}})\left(\frac{\hat{\delta}_{js\tau} + \hat{\delta}_{jst}}{2}\right)$$
$$+ \sum_{j=1}^{20}\left(\frac{\overline{D^j_{s\tau}} + \overline{D^j_{st}}}{2}\right)(\hat{\delta}_{js\tau} - \hat{\delta}_{jst}).$$

The first term on the right-hand side of Equation 5 is the part of the change in the mean log wage gap explained by changes over time in the mean observed skill gap between home-based and onsite workers. The second term on the right-hand side of Equation 5 is the part of the change in the mean log wage gap explained by changes over time in the returns to observed skills, given the time-averaged mean observed skill gap between home-based and onsite workers. The third term on the right-hand side of Equation 5 is the part of the change in the mean log wage gap explained by changes over time in the occupational distribution of home-based employment, given the average of the occupation-specific home-based wage penalties at dates t and τ. Finally, the fourth term on the right-hand side of Equation 5 is the part of the change in the mean log wage gap that is explained by changes over time in the home-based wage penalties *within* occupation groups.

Table 5 presents the results from the statistical decompositions in Equations 4 and 5, separately for males and females, for the 1980–90 and 1990–2000 periods. The upper panel of the table indicates that, for both sexes, the home-based share of wage and salary employment rose by about two-tenths of a percentage point between 1980 and 1990 and by a full half percentage point between 1990 and 2000. Changes over time in the occupational distribution of wage and salary employment can account for 24 (12) percent of the growth in the aggregate male (female) home-based employment share between 1980 and 1990. However, such compositional shifts explain essentially none of the more rapid growth in the aggregate home-based employment shares between 1990 and 2000. Thus, the vast majority of the growth in the home-based share of wage and salary employment in recent decades is explained by increases in the frequency of home-based employment *within* occupation categories.

The lower panel of the table decomposes the changes over time in the mean log wage gap between home-based and onsite workers. Home-based workers of both sexes made wage gains relative to their onsite counterparts in both decades, with larger gains occurring over 1990–2000. Depending on the decade, 30 to 40 percent of the relative wage gains of male home-based workers can be explained by gains in their observable skills. For females, gains in measured skills account for only 10 to 25 percent of the relative wage gains of home-based workers. Changes in the returns to observed human capital explain essentially none of the relative wage gains made by home-based workers of either sex. Thus, depending on decade and gender group, at least 60 percent and as much as 90 percent of the relative wage gains of home-based workers is accounted for by changes in either the occupational distribution of home-based workers or home-based wage penalties *within* occupation groups. The last two rows of Table 5 clearly indicate that, for both sexes in both decades, reductions in home-based wage penalties within occupations accounted for the vast majority of these residual relative wage gains of home-based workers. In summary, the main messages of Tables 4 and 5 are that (i) the pattern of rising (declining) home-based employment shares (wage penalties) in recent decades occurred within almost all gender-occupation groups and (ii) these within-group changes account for most of the growth (decline) in the aggregate home-based employment share (wage penalty).

Table 5

Decompositions of changes over time in the home-based employment share and the mean log wage gap between home-based and onsite workers, by gender and time period

	Males		Females	
	1980–1990	1990–2000	1980–1990	1990–2000
Total change in home-based employment share	0.0025	0.0046	0.0016	0.0051
Part due to changes in the composition of wage and salary employment across occupations	0.0006	−0.0002	0.0002	0.0003
Part due to changes in home-based employment shares within occupations	0.0019	0.0048	0.0014	0.0048
Total change in mean log wage gap between home-based and onsite workers	0.1904	0.3276	0.1139	0.208
Part due to changes in the mean observed skill gap between home-based workers and onsite workers	0.0561	0.1338	0.0101	0.0536
Part due to changes in the returns to observed skills, given the mean gap in observed skills	−0.0005	−0.0019	−0.0181	0.0157
Part due to changes in the composition of home-based employment across occupations	0.0145	0.0421	0.0172	0.0039
Part due to changes in home-based wage penalties within occupations	0.1203	0.1536	0.1047	0.1348

Note: The decomposition in the upper panel of the table uses the formula in Equation 4 of the paper. The decomposition in the lower panel of the table uses the formula in Equation 5 of the paper. Both decompositions use the 20 mutually exclusive and exhaustive occupation categories shown in Tables 2 and 4.

D. Can IT Explain the Variation in Home-Based Employment Shares and Wage Penalties?

The empirical evidence so far is consistent with the view that broad-based reductions in employer costs of providing home-based jobs have been the main source of growth in the home-based employment share in recent decades. What might have caused these costs to fall? Advances in IT are an obvious possibility. Indeed, recent studies have argued that IT innovations have contributed to the widening of educational wage differentials (Autor, Katz, and Krueger 1998), the rise in female employment and decline in male-female wage differentials (Weinberg 2000), and the adoption of new production methods and organizational practices (Bresnahan, Brynjolfsson, and Hitt 2002) in recent decades.

If IT gains were the main reason that employers' costs of offering home-based jobs fell, one would expect larger increases in home-based employment shares and larger declines in home-based wage penalties to have occurred in gender-occupation categories where these improvements could be utilized more intensively on the typical job. For example, the development and diffusion of technologies allowing electronic file-sharing should have reduced productivity losses and wage penalties from working at home, and therefore should have facilitated growth in home-based work, more for jobs that can readily use these technologies (such as insurance sales agents) than for jobs where these technologies have little application (such as massage therapists). In addition, one might expect these effects of IT advances to be larger in jobs where less face-to-face interaction with customers or coworkers is required.

To test these hypotheses, I estimate the regression models in Equation 3. These models seek to explain the variation across gender × occupation × year cells in home-based employment shares and home-based wage penalties with across-cell variation in (i) the rate of on-the-job IT use and (ii) an interaction between on-the-job IT use and a variable measuring how much face-to-face interaction the job requires — after controlling for gender-occupation fixed effects and year fixed effects. Including gender-occupation fixed effects controls for relatively permanent differences in job tasks and production technologies that make some jobs easier to perform from home than others. Including year fixed effects removes any general time trend in home-based employment shares or home-based wage penalties, whatever the source. The estimated slope coefficients therefore measure how home-based employment shares and home-based wage penalties have been correlated with on-the-job IT use, and how these effects have been moderated by the extent of required face-to-face interaction on the job, after controlling for common time trends and gender-occupation-specific heterogeneity.

Estimating Equation 3 requires a gender × occupation × year cell-specific measure of the rate of on-the-job IT use and a gender × occupation cell-specific measure of the fraction of jobs that require less than weekly face-to-face discussion with customers or coworkers. I compute several gender × occupation × year cell-specific measures of on-the-job IT use from samples of all wage and salary workers aged 25–64 in the October 1984, October 1993, and September 2001 CPS. The supplements to these particular CPS surveys asked questions about computer and IT use on the job, with the latter two supplements inquiring about a variety of specific uses including database management, spreadsheet programs, and email and internet communication. Fortuitously, the time between these supplements corresponds reasonably closely to the ten-year intervals separating the censuses.

Table 6 displays rates of on-the-job IT use by gender-occupation group and survey year. The first three columns show the fraction of workers in the cell who used a computer on the job for any purpose. On-the-job computer use varied greatly across gender-occupation groups in each year, with much higher usage in professional, managerial, administrative, and sales occupations. Over time, computer use at work has risen dramatically, although the magnitude and timing of this growth has varied across gender-occupation groups. The remaining columns show the fraction of workers in the cell who used a computer on the job for database management or spreadsheet programs (Columns 4 and 5) and for email or internet (Columns 6 and 7) in 1993 and 2001. These narrower measures of on-the-job IT use may identify "IT-intensive" gender-occupation categories more accurately, as individuals who used a computer only for inessential activities such as games, music, calendars, or time-keeping are not counted. On-the-job IT use is necessarily lower by these measures, but the general pattern of variation across gender-occupation groups and over time appears similar to the broader measure.

I compute a gender-occupation-specific measure of the importance of in-person interactions on the job using a single cross-section of data from O*NET, the database that succeeded and expanded upon the DOT. O*NET combines survey responses of both job incumbents and professional occupational analysts to describe the required skills, necessary prior training, detailed job tasks, and context of work for over 500 specific occupations.[17] One element of work context on which data are collected and that might influence the share of jobs in the occupation that are home-based is how often the work "requires face-to-face discussion with individuals and within teams." The fraction of responses in five ordinal categories, ranging from "every day" to "never," is available for each occupation. Using these data, I compute the share of jobs that require *less than weekly* face-to-face discussion in each of my more aggregated gender-occupation groups.[18] The percentage of jobs requiring less than weekly face-to-face discussion ranges from 0.6 percent for male lawyers and judges to 26.5 percent for female retail sales workers. The unweighted mean (standard deviation) across all gender-occupation groups is 11.7 (6.5) percent. In general, professional and managerial occupations are the least likely to require only infrequent face-to-face interaction.

Because the share of jobs in each gender-occupation group requiring less than weekly face-to-face discussion is measured at only one point in time, the main effect of this variable on home-based employment shares or home-based wage penalties cannot be identified separately from the gender-occupation fixed effect. However,

17. The data used in this study come from O*NET 12.0, which was published in June 2007. The O*NET database first became available in electronic form in 1999, but with more limited data. The DOT never collected the relevant context of work data that is contained in O*NET and also used a different occupational classification system. Consequently, unlike some recent studies such as Autor, Levy, and Murnane (2003), I do not use the DOT data.

18. Specifically, I compute the employment-weighted average of the fraction of jobs that require less than weekly face-to-face discussion across all of the individual occupations in an occupation group, separately by gender and for each of the 20 occupation categories.

Table 6
On-the-job IT use, by gender-occupation category and year

	Share of workers who use a computer on the job for:						
	Any Purpose			Databases or Spreadsheets		Email or Internet	
Occupation category	1984	1993	2001	1993	2001	1993	2001
A. Males							
Managerial, business	0.452	0.734	0.827	0.444	0.655	0.222	0.721
Engineers, scientists	0.587	0.866	0.918	0.522	0.775	0.368	0.846
Healthcare practitioners	0.358	0.666	0.755	0.283	0.431	0.086	0.542
Teachers, educators	0.367	0.623	0.846	0.236	0.569	0.120	0.733
Arts, media, social service	0.257	0.623	0.785	0.220	0.487	0.121	0.686
Lawyers, judges	0.302	0.667	0.926	0.211	0.549	0.190	0.897
Technicians	0.574	0.734	0.789	0.327	0.538	0.225	0.631
Sales supervisors & reps	0.328	0.639	0.782	0.297	0.549	0.150	0.633
Retail sales	0.184	0.419	0.517	0.111	0.249	0.060	0.266
Office support	0.576	0.801	0.793	0.343	0.546	0.196	0.554
Mail & shipping clerks	0.277	0.555	0.559	0.205	0.330	0.114	0.403
Protective service	0.221	0.457	0.564	0.159	0.299	0.056	0.353
Food or cleaning service	0.037	0.080	0.150	0.019	0.069	0.007	0.082
Health or personal service	0.057	0.154	0.295	0.028	0.140	0.005	0.188
Farming, forestry, fishing	0.015	0.048	0.137	0.008	0.083	0.002	0.096
Mechanics & repairers	0.150	0.310	0.430	0.088	0.208	0.058	0.262
Construction trades	0.040	0.073	0.148	0.026	0.081	0.012	0.090
Extractive, precision production	0.167	0.361	0.412	0.129	0.221	0.058	0.234
Machine operators	0.097	0.211	0.268	0.055	0.109	0.015	0.123
Vehicle operators	0.035	0.128	0.167	0.014	0.073	0.009	0.074
B. Females							
Managerial, business	0.494	0.794	0.862	0.470	0.675	0.254	0.714
Engineers, scientists	0.668	0.838	0.917	0.544	0.719	0.389	0.850
Healthcare practitioners	0.251	0.555	0.740	0.198	0.333	0.065	0.422
Teachers, educators	0.318	0.531	0.766	0.142	0.440	0.062	0.614
Arts, media, social service	0.260	0.600	0.777	0.240	0.425	0.144	0.617
Lawyers, judges	0.277	0.712	0.940	0.128	0.504	0.216	0.865
Technicians	0.430	0.632	0.722	0.273	0.378	0.122	0.447
Sales supervisors & reps	0.416	0.670	0.771	0.296	0.494	0.158	0.573
Retail sales	0.118	0.295	0.389	0.069	0.189	0.019	0.208
Office support	0.498	0.827	0.837	0.353	0.531	0.178	0.563
Mail & shipping clerks	0.510	0.736	0.737	0.306	0.421	0.167	0.489
Protective service	0.202	0.404	0.526	0.147	0.232	0.058	0.296
Food or cleaning service	0.020	0.080	0.159	0.008	0.065	0.004	0.069
Health or personal service	0.056	0.152	0.274	0.033	0.118	0.014	0.132

(continued)

Table 6 *(continued)*

	Share of workers who use a computer on the job for:						
	Any Purpose			Databases or Spreadsheets		Email or Internet	
Occupation category	1984	1993	2001	1993	2001	1993	2001
Farming, forestry, fishing	0.020	0.072	0.340	0.035	0.198	0.000	0.183
Mechanics & repairers	0.382	0.601	0.632	0.200	0.373	0.149	0.466
Construction trades	0.174	0.231	0.277	0.099	0.091	0.033	0.118
Extractive, precision production	0.120	0.259	0.342	0.080	0.167	0.030	0.199
Machine operators	0.044	0.139	0.251	0.037	0.095	0.010	0.085
Vehicle operators	0.068	0.168	0.215	0.052	0.078	0.012	0.094

Note: Rates of on-the-job IT use are calculated for samples of nonself-employed, civilian workers aged 25–64 from the October 1984, October 1993, and September 2001 Current Population Surveys, using the CPS supplement individual sample weights.

by including an interaction between this variable and the (time-varying) rate of on-the-job IT use in the gender-occupation category in Equation 3, I can investigate whether the effect of on-the-job IT use on home-based employment shares or home-based wage penalties is moderated by how much face-to-face discussion is required on the job.

Table 7 reports weighted least squares estimates of Equation 3, where the inverse of the estimated standard error of the dependent variable (the cell-specific home-based employment share or home-based wage penalty) is used as the weighting variable. Panel A shows the results when the share of workers in the gender$\times$occupation$\times$year cell who use a computer on the job for any purpose is used as the measure of "IT intensity." While the point estimates suggest that greater on-the-job IT use is correlated with higher home-based employment shares and smaller (less negative) home-based wage penalties, these relationships are not statistically significant at conventional levels.

But, as discussed above, the share of workers who report using IT on the job for specific tasks such as database management or email may be a better measure of each cell's true "IT intensity." Because the CPS first collected task-specific on-the-job computer use data only in 1993, I had to impute 1984 values for each gender-occupation cell. To impute the shares of workers who used a computer for database management or spreadsheets in 1984, I assumed that within each gender-occupation category the ratio of database or spreadsheet users to all on-the-job computer users was the same in 1984 as in 1993. In contrast, I imputed the share of workers who used a computer on the job for email or internet to be zero in 1984 for every gender-occupation group, because commercial internet service providers did not even exist until the late 1980s.

Table 7
How on-the-job IT use is related to home-based employment shares and home-based wage penalties across gender×occupation×year cells

	Dependent variable:			
	Home-Based Employment Share		Home-Based Wage Penalty	
A. "IT Share" is fraction in cell who use computer on job for any purpose				
IT Share	0.0107	0.0093	0.0858	0.1449
	(0.0060)	(0.0061)	(0.1205)	(0.1246)
IT Share × Share of jobs requiring less than weekly face-to-face discussion		0.0480		−1.765
		(0.0531)		(1.086)
R^2	0.910	0.911	0.880	0.884
B. "IT Share" is fraction in cell who use computer on job for databases or spreadsheets				
IT Share	0.0225	0.0168	0.245	0.2875
	(0.0059)	(0.0062)	(0.1225)	(0.1343)
IT Share × Share of jobs requiring less than weekly face-to-face discussion		0.1845		−1.277
		(0.0769)		(1.637)
R^2	0.921	0.926	0.885	0.886
C. "IT Share" is fraction in cell who use computer on job for email or internet				
IT Share	0.0112	0.0072	0.1268	0.1498
	(0.0029)	(0.0033)	(0.0596)	(0.0708)
IT Share × Share of jobs requiring less than weekly face-to-face discussion		0.1092		−0.5947
		(0.0461)		(0.9779)
R^2	0.921	0.927	0.886	0.887

Note: The table reports the estimated slope coefficients and R^2 values from weighted least squares regressions explaining the variation in home-based employment shares and home-based wage penalties across gender×occupation×year cells. The weight received by each cell is given by the inverse of the estimated standard error of the dependent variable (home-based employment share or home-based wage penalty) for that cell. All regressions have 120 observations (2 genders × 20 occupation groups × 3 census years) and include both gender-occupation fixed effects and year fixed effects. Standard errors are shown in parentheses.

The lower panels of Table 7 show that one obtains qualitatively different estimates of Equation 3 using these narrower measures of on-the-job IT use. In Columns 1 and 3, which do not include the interaction term between on-the-job IT use and the share of jobs that require less than weekly face-to-face discussion, the results clearly indicate that home-based employment shares tended to be higher and home-based wage penalties tended to lower (less negative) in cells with higher rates of on-the-job IT use. Again, note that these results hold after controlling for both fixed gender-occupation effects and fixed year effects. Thus, the results indicate that home-based employment shares (wage penalties) grew (shrank) by larger amounts in gender-occupation categories that experienced greater growth in (task-specific measures of) on-the-job IT use.

When the interaction term is added (Columns 2 and 4), its estimated coefficient is positive and significant in the regression explaining home-based employment shares but is negative and insignificant in the regression explaining home-based wage penalties. In both regressions, the main effects of on-the-job IT use on these outcomes are basically unchanged. These results imply that a given increase in on-the-job IT use has tended to be accompanied by a larger increase in the home-based employment share—but not by a larger decline in the home-based wage penalty—in gender-occupation cells where a larger share of jobs require less than weekly face-to-face interaction. Given this mixed result, the main findings from Table 7 are simply that the growth in home-based employment shares and the decline in home-based wage penalties have been more pronounced in gender-occupation cells with greater growth in on-the-job IT use.

The results in Table 7 are robust to various changes in variable measurement, estimation method, and model specification. For example, the results are qualitatively unchanged when I reestimate the models using a different measure of on-the-job IT use or alternative imputation methods for the 1984 values.[19] Likewise, I obtain comparable results when I reestimate the models by unweighted ordinary least squares. Finally, the results are largely unchanged when I estimate the models without year fixed effects, thereby attributing *all* of the time-series growth (decline) in home-based employment shares (wage penalties) to the growth in on-the-job IT use over time.

In addition, I have checked the robustness of the full set of results reported in the paper in several ways. For example, the results are qualitatively unchanged when I estimate all of the empirical models using samples limited to workers aged 25–55. Likewise, I always obtain essentially identical results to those reported above when I use alternative 1 percent random subsamples of PUMS households with zero home-based workers. Finally, all of the results are virtually unchanged if I use different reasonable rules for imputing topcoded earnings or if I simply drop the topcoded earnings observations from the analyses.

19. In particular, I obtain similar results when I use the fraction of workers who used a computer on the job for word processing as an alternative measure of on-the-job IT use. I also get similar results when I impute 1984 values for the shares of workers using IT on the job for a particular task by assuming that the gender-occupation-specific growth rates in the shares between 1984 and 1993 equaled the *observed* gender-occupation-specific growth rates in the shares between 1993 and 2001.

V. Conclusion

This paper has used labor market data from the 1980–2000 U.S. Censuses of Population, supplemented by on-the-job IT use data from the CPS and data on the extent of required face-to-face discussion on the job from O*NET, to analyze how and why the home-based share of employment and the wage penalty on home-based jobs changed between 1980 and 2000. The main findings are: (i) the overall home-based employment share nearly doubled and the mean home-based wage penalty fell by about 30 percentage points over these two decades; (ii) the rise in the home-based employment share and decline in the home-based wage penalty occurred in nearly all major gender-occupation categories and changes in the occupational composition of overall (home-based) employment account for little of the aggregate change in the home-based employment share (wage penalty); and (iii) increases in home-based employment shares and declines in home-based wage penalties were larger in gender-occupation cells that saw greater growth in on-the-job IT use for specific work-related tasks.

These findings suggest that falling employer costs of offering home-based work arrangements have been the main factor behind the growth in home-based wage and salary employment over the last several decades and that IT advances were probably an important source of these falling costs. Future research should examine how continued advance and diffusion of IT since 2000 have affected home-based employment shares and home-based wage penalties. Perhaps equally importantly, future research should study how IT gains have influenced other margins of labor supply decisions, including work schedule choices, couples' colocation decisions, and mothers' employment behavior following childbirth.

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