The Growth in Home-Based Wage and Salary Employment in the United States, 1980-2000: How Much and Why?

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Abstract

This study quantifies the growth in home-based employment among prime-age, civilian workers in the United States between 1980 and 2000 and analyzes how the wage penalty on home-based wage and salary jobs evolved over these twenty years. Home-based employment grew much more rapidly than on-site employment during this period, especially among wage and salary workers. At the same time, the mean wage penalty suffered by wage and salary workers on home-based jobs fell dramatically over this period. These patterns hold not only in the aggregate but also within almost all occupation categories, and little of the aggregate change in the home-based employment share or the home-based wage penalty is explained by change in the occupational composition of employment. These findings suggest that widespread reductions in employers' costs of providing home-based work arrangements were the main reason for the growth in home-based employment in the last several decades. The paper also shows that the relationship between the home-based wage penalty and the probability that a worker uses a computer at work has changed markedly over time, in ways that suggest that IT innovations have had significant impacts on worker labor market productivity both in the workplace and at home.

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 broader forces operating over this time period potentially can explain this dramatic growth in home-based employment. For example, 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 of home production tasks within the family. Also, major advances in information and communications technology that may have reduced the costs of providing home-based work arrangements occurred during these years. Finally, shifts in the occupational composition 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 1988; Presser and Bamberger 1993; Edwards and Field-Hendry 2001, 2002; Pabilonia 2005; Schroeder and Warren 2005) all have analyzed its determinants or its wage consequences at a point in time. While valuable, these studies offer no insight into why home-based employment has expanded so rapidly in recent years. The present paper seeks 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 employment among wage and salary workers and the concomitant changes in the wages of home-based employees relative to observationally equivalent on-site workers.

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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.

I find that the rapid growth in home-based wage and salary employment has been 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 and home-based wage penalties have varied substantially across skill groups but that only small fractions of the aggregate growth in the home-based employment share and the aggregate decline in the home-based wage penalty can be explained by compositional shifts favoring skill groups with high propensities towards and low penalties from home-based work. These results strongly suggest that widespread reductions in employer costs of providing home-based work arrangements have been the predominant force behind the growth in home-based employment since 1980.

Advances in information technology (IT) are a natural suspect as a source of falling employer costs of providing home-based work arrangements. Such advances seem likely to have had a larger impact on relative productivity at home in some occupations than in others. Thus, if IT innovation was the primary cause of the increase in home-based employment and if the elasticity of supply into home-based employment was similar across all occupations, one would expect changes in the home-based employment share and the home-based relative wage to have been positively correlated across occupations. In the census data, I find such a positive correlation between 1990 and 2000 but not in the preceding decade.

I also examine the link between relative home-based productivity and (one component of) IT more directly by analyzing the evolution of the relationship between the home-based wage penalty and on-the-job computer use. For this analysis, I augment the census samples with predicted probabilities of computer use at work derived from estimates based on Current Population Survey (CPS) supplement data from 1984, 1993, and 2001. I find that between 1980 and 1990 the home-based wage penalty fell most for workers with the *lowest* probability of using a computer at work but that in the following decade the home-based wage penalty fell most for workers with the *highest* probability of using a computer at work. I argue that this pattern is quite consistent with IT innovation having played a significant role in the evolution of home-based employment.

The remainder of this paper proceeds as follows. Section 2 discusses the census data and quantifies in more detail the growth in home-based employment in the U.S. in recent decades. Section 3 argues, using the theory of compensating differentials, that alternative potential explanations for the rapid growth in the home-based employment share have distinct predictions for how the wage penalty on home-based jobs should have changed in recent years. Section 4 presents initial estimates that illustrate the sharp decline in the wage penalty on home-based jobs between 1980 and 2000. Section 5 investigates the extent of heterogeneity across occupation groups in the home-based employment share and the home-based wage penalty and the correlation across occupation groups between changes in the home-based employment share and changes in the home-based wage penalty. Section 6 examines the relationship between the home-based wage penalty and on-the-job computer use and the evolution of this relationship over time. Concluding remarks follow in the final section.

II. Data

The empirical analyses use data from the 5% 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 all others as on-site 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 very 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% 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. In the 1980 census, individuals who reported wage and salary income above $75,000 had their reports topcoded at $75,000; for these topcoded observations, I multiply the topcoded income by 1.4 before computing

[2] In fact, data from the May 2001 Current Population Survey (CPS) indicate that 19.8 million workers do *some* work at home at least once a week. This number is taken from the BLS 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.

the hourly wage.[4] 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 (as well as 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 to the extent that the durability of home-based jobs has 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 presents the evidence for this group as a whole. While employment of on-site workers grew by 44.1% between 1980 and 2000 (from almost 69.9 million to around 100.8 million), employment of home-based workers grew by a much larger 115.3% (from 1.58 million to 3.41 million) over the same period.[6] As a result, the home-based employment share grew from 2.21% in 1980 to 3.27% in 2000.

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[4] The census bureau replaced reported wage and salary incomes above the topcode levels in the 1990 and 2000 censuses ($140,000 and $175,000, respectively) with the state median (in 1990) or state mean (in 2000) income level among individuals with wage and salary income in excess of the topcode. I do not adjust income for individuals who reported wage and salary income above the topcode in these years.

[5] For details see Farber (1999) and the articles in the special October 1999 issue of the *Journal of Labor Economics*.

[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 over the 1980-2000 period.

These overall numbers mask substantial differences between wage and salary employees and the self-employed in both the level and the growth of home-based employment. These differences are shown in the lower panels of Table 1. Among wage and salary workers, home-based employment has been very rare historically but has grown at an extremely rapid rate in recent decades. In 1980, fewer than 1% (about 480,000 out of 64.1 million) of all prime-age, civilian wage and salary workers were home-based. Since then, home-based wage and salary employment grew by 67.6% between 1980 and 1990 and by 67.2% between 1990 and 2000, yielding a 180% growth rate over the entire period. This dwarfs the 44.4% growth rate in on-site wage and salary employment over the same twenty years. In contrast, among the self-employed, home-based employment has been much more common (though still unusual) historically but has grown less rapidly in recent years. In 1980, almost 15% (about 1.1 million out of 7.42 million) of all prime-age, civilian self-employed workers were home-based. Home-based self-employment grew by 61.9% between 1980 and 1990, similar to the rate for home-based wage and salary workers, but then grew by only 15.6% between 1990 and 2000, yielding an 87.1% growth rate over the two decades. Although this is larger than 42% growth in on-site self-employment over the same period, the difference is not nearly as dramatic as for wage and salary employment.

For several reasons, I restrict attention to the growth in home-based wage and salary employment in the remainder of the paper. First, the distinct difference in the growth rates of home-based employment among wage and salary workers versus the self-employed, at least between 1990 and 2000, suggests that the forces causing growth in home-based employment may have differed between the self-employed and wage and salary sectors. Thus, it makes sense to analyze the two sectors 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 constant parametric wage given her skills, (ii) observed average hourly earnings are a good proxy for this (constant) marginal wage, and (iii) there exists a market-determined equilibrium (implicit) price for the nonwage 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

The theory of compensating differentials provides a useful framework for distinguishing among the possible causes of the dramatic growth in home-based wage and salary employment in recent decades.[7] "Home-basedness" is a nonwage job attribute for which both workers' valuations and employers' costs of provision are presumably heterogeneous. "Home-basedness" is a particularly valuable attribute for individuals with high opportunity costs of leaving or spending time outside the home. At the same time, "home-basedness" can be provided at lower cost on jobs that do not require team production, direct supervision, or proximity to complementary but physically immobile capital inputs.

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

Consider a competitive labor market for a homogeneous skill level composed of workers with varying valuations of working at home and employers with varying costs of offering home-based work arrangements. Let W_h and W_o denote, respectively, the market wage rates for home-based work and on-site work so that $\pi \equiv W_h - W_o$ is the wage penalty (or premium, if positive) for home-based work. In general, the share of workers supplying labor to home-based jobs will be an increasing function of π; as the wage penalty for home-based work shrinks (i.e., as π becomes less negative), more workers will seek home-based jobs. On the other hand, the share of jobs that employers are willing to make home-based is a decreasing function of π; as the wage savings on home-based jobs shrinks (i.e., as π becomes less negative), employers will offer fewer home-based jobs. In equilibrium, π must adjust so that the fraction of workers seeking home-based jobs equals the fraction of jobs that employers choose to make home-based.[8]

The theory of compensating differentials predicts that the distributions of worker valuations of "home-basedness" and employer costs of providing "home-basedness" will jointly determine the equilibrium value of π and that, in equilibrium, home-based jobs will be held by workers who value "home-basedness" most and will be provided by employers who can offer "home-basedness" at lowest cost. If providing home-based work arrangements were costly for all jobs, a wage penalty would exist for home-based work in equilibrium, all else equal.

Within this framework, the dramatic growth in the home-based *share* of wage and salary employment in recent decades could be explained either by outward shifts in the relative supply of labor to home-based jobs or by outward shifts in the relative demand

[8] Equilibrium also requires that the wage levels, W_h and W_o, adjust so that the aggregate quantity of labor supplied equals the aggregate quantity of labor demanded.

for labor in home-based jobs. Changes over time in the demographic composition of the labor force towards groups that value home-based work arrangements more highly, which may have occurred with the rise in female labor force participation, would have caused such outward supply shifts. Increasing valuations of home-based work over time within demographic groups, perhaps resulting from changes in preferences, income, or family structure, would have had the same effect. On the other hand, reductions in firms' nonwage costs of providing home-based work arrangements, a possible consequence of recent advances in IT, would have caused outward shifts in the relative demand for labor in home-based jobs. Similarly, changes in the industrial or occupational structure of U.S. employment in favor of sectors that can offer home-based jobs more cheaply would have caused outward demand shifts.

Supply-side versus demand-side explanations for the growth in the home-based employment share have opposite implications for how the wage penalty for home-based jobs should have changed over time. In particular, if supply-side factors were dominant, then the wage penalty for home-based work should have increased in recent decades. On the other hand, if demand-side factors were dominant, then the wage penalty for home-based work should have decreased in recent decades. Thus, an empirical analysis of how the wage penalty associated with home-based employment has changed in recent decades can help discriminate among alternative explanations for the growth in home-based wage and salary employment. I pursue this analysis below.

IV. The Wage Penalty on Home-Based Jobs, 1980-2000

Before reporting estimates of the wage penalty on home-based jobs, Table 2 presents descriptive statistics for wages and human capital characteristics of both on-site and home-based workers in each census year. The samples of wage and salary workers are the same as earlier, but with the added restriction that only observations with real hourly wages between $1 and $150 are included. The table reveals a number of interesting facts. The mean log real wage was much lower among home-based workers than among on-site workers in 1980 but, by the year 2000, the mean log real wage actually was higher among home-based workers. This reversal is the result of an approximately constant mean log real wage among on-site workers between 1980 and 2000 coupled with a rapidly rising mean log real wage among home-based workers over this same time period. Wage dispersion was much higher among home-based workers than among on-site workers in all years.[9]

The remainder of the table illustrates mean human capital differences between home-based workers and on-site workers at a point in time as well as changes in the mean human capital of both groups of workers over time. I comment here on some of the more striking patterns. First, the fraction of home-based workers that are female has *decreased* over time, despite the significant increase over time in the fraction female among on-site workers. Second, while home-based workers were much more likely than on-site workers to work on a part-time or part-year basis or to be disabled in 1980, these differences had either diminished substantially (in the case of part-time hours) or disappeared entirely (in the cases of part-year weeks worked and disability status) by 2000.[10] Third, home-based workers were considerably more educated than on-site workers by 2000, even though the distribution of educational attainment was very similar

[9] Wage dispersion increased over the sample period for males and females separately but did not rise much for both sexes combined because the male-female mean log wage gap declined over the same period.
[10] The rise in the reported *level* of disability in 2000 reflects changes in the wording of the census question about disability status, but it does not alter the observation that the frequency of disability among home-based workers *relative* to the frequency among on-site workers declined between 1980 and 2000.

for both groups in 1980. Finally, differences in the occupational distribution of home-based workers and on-site workers changed noticeably between 1980 and 2000. Relative to the occupational distribution for on-site workers, that of home-based workers shifted disproportionately towards managerial, scientific, and sales jobs and away from farming and service occupations. Not surprisingly, there exist pronounced differences in the occupational distribution of on-site and home-based workers in all years.

The picture that emerges from Table 2 is that home-based wage and salary workers gained substantially on on-site workers in their observable skills between 1980 and 2000. In particular, home-based workers became *relatively* more educated, more concentrated in high-wage occupations, less likely to have a disability, and less likely to be only partially employed in the labor market. These relative gains in the observed skills of home-based workers likely explain part of their relative wage gains over this period, making it important to control for observed skills in estimating the wage penalty on home-based jobs.

To obtain estimates of the home-based wage penalty at a point in time, I initially estimate models of the form

$$\ln W_{it} = X_{it}\beta_t + \sum_{j=1}^{19}\gamma_{jt}D_{ijt} + \delta_t H_{it} + \varepsilon_{it}, \quad t = 1980, 1990, 2000 \qquad (1)$$

for the samples of 25-64 year old wage and salary workers in civilian jobs. In equation (1), *i* indexes individuals, *t* indexes census years, W_{it} is the real hourly wage, X_{it} is a vector of observable characteristics that affect wages, D_{ijt} is an indicator for employment in occupation category *j*, H_{it} is an indicator for holding a home-based job, ε_{it} is a disturbance term, and β_t, $\{\gamma_{jt}\}_{j=1}^{19}$, and δ_t are parameters to be estimated. The parameter of primary interest is δ_t, which (approximately) measures the percentage wage penalty on a home-based job in year *t*, holding all other observables constant.

Ordinary least squares estimates of δ_t will be biased estimates of the true compensating differential for a home-based job in year *t* if the unobserved determinants of an individual's wage (productivity), ε_{it}, are correlated with whether an individual has a home-based job, H_{it}. There are at least two reasons to expect such a correlation. On the one hand, as Brown (1980) and others have noted, workers with high unobserved productivity have high full income (given their observed skills) and are likely to spend part of their greater full income on desirable job attributes. Thus, if "home-basedness" is generally considered desirable, workers with high unobserved productivity should be more likely to select into home-based employment and therefore $\hat{\delta}_t$ will be an upward biased estimate of the true compensating differential (i.e., the estimated wage penalty will be too small). On the other hand, a worker with a home-based job avoids the fixed costs of on-site work (Edwards and Field-Hendry 2001, 2002) and also may be able to perform some home production activities while doing market work from home. These nonwage benefits of a home-based job are more likely to outweigh the wage penalty from a home-based job for workers with low market wage opportunities, which suggests that workers with *low* unobserved productivity should be more likely to select into home-based employment. This type of selection will cause $\hat{\delta}_t$ to be a downward biased estimate of the true compensating differential. Because these two potential sources of bias work in opposite directions, the sign of any bias in OLS estimates of δ_t is unclear *a priori*.[11]

Since I seek to shed light on the relative importance of supply-side versus demand-side factors in explaining the growth in the home-based employment share in recent decades, the *change* in the wage penalty on home-based jobs over time is of greater interest than its level at a point in time. Even if the estimated wage penalty on home-based jobs at a point in time is a biased estimate of the true compensating differential for the reasons described above, the change in the estimated wage penalty over time will measure the true change in the compensating differential accurately *if* the bias in the estimated wage penalty is constant over time. Of course, it is far from clear that the bias has been constant over time. In particular, Table 2 suggests that observable skills rose much more among home-based workers than among on-site workers in recent decades. If home-based workers made similar relative gains in unobserved skills, the change over time in the estimated home-based wage penalty will overstate the relative wage gains enjoyed by a home-based worker of *fixed* skill, because part of the reduction in this penalty will reflect unmeasured skill improvements among home-based workers over time. Later, I address this concern to some extent by estimating models that allow the home-based wage penalty to vary across workers with different observed skills. But, in all of the estimates, part of the change over time in the estimated wage penalty may reflect change in the unobserved skill of home-based workers (relative to on-site workers)

[11] Ideally, one would like to find a valid instrument for holding a home-based job and then estimate (1) by instrumental variables methods. However, it is difficult to think of a variable available in the census data that has strong predictive power for whether a worker has a home-based job but that does not directly affect the worker's wage opportunities.

rather than a pure change in the equilibrium implicit price of "home-basedness" for a worker of fixed skill.

Table 3 presents OLS estimates of (1) for 1980, 1990, and 2000. The explanatory variables include a standard set of demographic and human capital controls in addition to the home-based job indicator. As a whole, these variables explain approximately 30% of the sample variation in log real wages in each census year. The estimated coefficients for all of the control variables have the expected signs and do not require extended discussion. In addition, the coefficients on most of the control variables are quite stable over time. The exceptions are the increase in the estimated return to education, the decline in the estimated male-female wage gap, and the reduction in the estimated wage costs of children for women between 1980 and 2000.[12]

The estimated wage penalty on home-based jobs fell precipitously between 1980 and 2000, mirroring the changes over time in the mean log real wage difference between home-based and on-site workers shown in Table 2. In 1980, the average log real wage difference between a home-based worker and an observationally equivalent on-site worker was $-.31$. By 1990, this wage penalty on home-based jobs had shrunk to $-.17$ and, by 2000, it had nearly disappeared. Thus, even after controlling for the relative gain in the observable skills of home-based workers, it is clear that a rise in the relative wage of home-based workers (or, equivalently, a decline in the wage penalty on home-based jobs) accompanied the growth in home-based employment share. This finding suggests that either reductions in employer costs of offering home-based jobs or compositional

[12] The estimated wage penalty associated with disability also declined between 1990 and 2000, but this is likely an artifact of the less stringent definition of disability used in the 2000 census.

shifts in employment favoring jobs that can be located at home at low cost were the dominant force behind the rapid growth in home-based employment.

V. Heterogeneity in the Home-Based Wage Penalty

The models estimated above impose the restriction that the wage penalty on home-based jobs is identical for all types of workers and jobs. However, it is plausible on theoretical grounds that the market compensating wage differential for home-based work varies across occupations, both because employers' costs of offering home-based work arrangements depend on the tasks that workers perform and because workers' valuations of working at home may vary with full income. In addition, in certain occupations (e.g., farming, clergy) some home-based workers may receive a substantial portion of their compensation in the form of employer-provided or employer-subsidized housing. In such occupations, one would expect to see a larger *wage* penalty for home-based employment.

If differences in the home-based wage penalty do exist across occupations, part of the drop in the average home-based wage penalty shown in Table 3 may result from relative growth (decline) in home-based employment in occupations with lower (higher) home-based wage penalties rather than from actual reductions in home-based wage penalties *within* occupations. Estimates that allow the home-based wage penalty to vary across occupations can be used to examine whether such compositional shifts were an important part of the explanation for the decline in the aggregate home-based wage penalty. Similarly, if there exist differences in the home-based employment share across occupations, then part of the increase over time in the average home-based employment share may be explained by relative growth (decline) in employment in occupations with high (low) propensities toward home-based work rather than from increases in home-based employment shares *within* occupations.

The three left-hand columns of Table 4 present, for each census year, the home-based employment share in each of 20 occupation categories. The hypothesis that home-based employment shares were equal across occupation categories is rejected at any conventional significance level in all three census years. Perhaps unsurprisingly, given the empirical observation that motivates this paper, the home-based employment share grew between 1980 and 2000 in most occupation groups. However, the rate of growth varied substantially across occupations. For example, the home-based share grew by over 500% for engineers and scientists, who rarely were home-based in 1980, while it fell in farming-related occupations, which had the highest home-based share in 1980.

To allow for heterogeneity in the wage penalty on home-based jobs, I estimate models of the form

$$\ln W_{it} = X_{it}\beta_t + \sum_{j=1}^{19}\gamma_{jt}D_{ijt} + \sum_{j=1}^{20}\delta_{jt}D_{ijt}H_{it} + \varepsilon_{it}, \quad t = 1980, 1990, 2000 \quad (2)$$

where all variables are as defined in (1) and $\left\{\delta_{jt}\right\}_{j=1}^{20}$ is a vector of occupation-specific home-based wage penalties in year *t*. Estimates of $\left\{\delta_{jt}\right\}_{j=1}^{20}$ for each census year are presented in the three right-hand columns of Table 4.[13] To save space, standard errors are

[13] In an unreported analysis, I instead allowed the home-based employment share and home-based wage penalty to vary across skill groups defined by the 32 mutually exclusive and exhaustive categories derived from the full set of interactions between two sexes, four education levels (less than a high school degree, exactly a high school degree, some college, and four years of college or more), and four age groups (25-34, 35-44, 45-54, and 55-64). The qualitative patterns that emerged from this analysis are quite similar to those shown in Table 4. The results of this analysis are available from the author upon request.

not reported.[14] Likewise, estimates of the coefficients on the other covariates in the model are not reported, although the estimates of β_t are very similar to those reported in Table 3. As was true for home-based employment shares, one easily rejects the hypothesis that the wage penalties on home-based jobs were identical across occupation categories in all census years. Comparing the estimated coefficients across census years reveals that the wage penalty for home-based employment shrank with the passage of time in every occupational category except for mechanics and repair workers between 1980 and 1990. By the year 2000, home-based workers in a few occupations actually earned higher average pay than observationally equivalent on-site workers.

I use standard decomposition techniques to assess the empirical importance of composition effects in explaining changes over time in the aggregate home-based employment share and aggregate home-based wage penalty. Let H_t denote the home-based share at date *t* among all wage and salary workers aged 25-64 and let H_{jt} denote the home-based share at date *t* within occupation category *j*. Then $H_t = \sum_{j=1}^{20} s_{jt} H_{jt}$, where s_{jt} is occupation group *j*'s share in total wage and salary employment at date *t*. The change in the average home-based employment share between dates *t* and τ can be decomposed as

$$H_\tau - H_t = \sum_{j=1}^{20} \left(s_{j\tau} - s_{jt}\right)\left(\frac{H_{j\tau} + H_{jt}}{2}\right) + \sum_{j=1}^{20} \left(\frac{s_{j\tau} + s_{jt}}{2}\right)\left(H_{j\tau} - H_{jt}\right). \qquad (3)$$

The first term in (3) is the part of the change in the aggregate home-based share that is explained by changes over time in the distribution of wage and salary workers across

[14] The standard errors fall in the .01-.04 range in all years for almost all occupations. The standard errors are somewhat larger for the occupation categories with the smallest employment shares and the lowest incidence of home-based work.

occupation groups, given the average occupation-specific propensities for home-based work at dates t and τ. The second term in (3) is the part of the change in the aggregate home-based share that is explained by changes over time in the propensities for home-based work *within* occupation groups.

Turning next to the home-based wage penalties, the empirical specification in (2) and well-known properties of least squares regression imply that the mean log wage for on-site workers at time t can be written as

$$\overline{\ln W_t^o} = \overline{X_t^o}\hat{\beta}_t + \sum_{j=1}^{20} \overline{D_{jt}^o}\hat{\gamma}_{jt} \equiv \overline{Z_t^o}\hat{\theta}_t^o \tag{4}$$

and the mean log wage for home-based workers at time t can be written as

$$\overline{\ln W_t^h} = \overline{X_t^h}\hat{\beta}_t + \sum_{j=1}^{20} \overline{D_{jt}^h}\left(\hat{\gamma}_{jt} + \hat{\delta}_{jt}\right) \equiv \overline{Z_t^h}\hat{\theta}_t^h . \tag{5}$$

Some simple algebra yields the following expression for the change in the mean log wage difference between home-based and on-site workers between dates t and τ:

$$\begin{aligned}\left(\overline{\ln W_\tau^h} - \overline{\ln W_\tau^o}\right) - \left(\overline{\ln W_t^h} - \overline{\ln W_t^o}\right) = {}& \left(\left(\overline{Z_\tau^h} - \overline{Z_\tau^o}\right) - \left(\overline{Z_t^h} - \overline{Z_t^o}\right)\right)\left(\frac{\hat{\theta}_\tau^o + \hat{\theta}_t^o}{2}\right) + \\ & \left(\left(\frac{\overline{Z_\tau^h} + \overline{Z_t^h}}{2}\right) - \left(\frac{\overline{Z_\tau^o} + \overline{Z_t^o}}{2}\right)\right)\left(\hat{\theta}_\tau^o - \hat{\theta}_t^o\right) + \\ & \left(\overline{Z_\tau^h} - \overline{Z_t^h}\right)\left(\left(\frac{\hat{\theta}_\tau^h + \hat{\theta}_t^h}{2}\right) - \left(\frac{\hat{\theta}_\tau^o + \hat{\theta}_t^o}{2}\right)\right) + \\ & \left(\frac{\overline{Z_\tau^h} + \overline{Z_t^h}}{2}\right)\left(\left(\hat{\theta}_\tau^h - \hat{\theta}_\tau^o\right) - \left(\hat{\theta}_t^h - \hat{\theta}_t^o\right)\right).\end{aligned} \tag{6}$$

The first term on the right-hand side of (6) is the part of the change in the mean log wage difference explained by changes over time in the mean gap in observed skills between home-based and on-site workers. The second term on the right-hand side of (6) is the part of the change in the mean log wage difference explained by changes over time in the returns to observed skills, given the average mean gap in observed skills between home-based and on-site workers. The third term on the right-hand side of (6) is the part of the change in the mean log wage difference explained by changes over time in the distribution of home-based employment across occupation categories, 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 (6) is the part of the change in the mean log wage difference that is explained by changes over time in the home-based wage penalties *within* occupation groups.[15]

Table 5 presents the results from the statistical decompositions in (3) and (6) for every combination of $t = 1980, 1990$, $\tau = 1990, 2000$, and $t < \tau$. The upper panel shows decompositions of the changes over time in the home-based employment share. The home-based share of wage and salary employment rose by over two-tenths of a percentage point between 1980 and 1990, by an additional one-half of a percentage point between 1990 and 2000, and hence by about seven-tenths of a percentage point over the full twenty year period.[16] Given the rarity of home-based employment among wage and salary workers, these changes represent a near doubling of the home-based share between 1980 and 2000. Changes over time in the distribution of wage and salary employment across occupation groups account for just 18% of the growth in the aggregate home-based share between 1980 and 1990 and just 4% of the growth in the aggregate home-based share between 1990 and 2000. Thus, the vast majority of the growth in the home-

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[15] The interpretations of the last two terms follow from the fact that the empirical specification in (2) restricts β_t to be identical for on-site and home-based workers.

[16] These numbers differ slightly from those implied by Table 1 because the samples now are limited to individuals with real hourly wages between \$1 and \$150.

based share is explained by increases in the frequency of home-based employment *within* occupation categories.

The lower panel of the table, which shows the decompositions of the changes over time in the mean log wage difference between home-based and on-site workers, tells a similar story. Growth in the mean log wage for home-based workers exceeded that for on-site workers by .187 between 1980 and 1990, by .283 between 1990 and 2000, and hence by .47 between 1980 and 2000. In all three time intervals, approximately one-third of these gains can be explained by growth in the observed skills of home-based workers relative to on-site workers. In contrast, changes in the returns to observed skills account for almost none of the relative wage gains of home-based workers. Thus, the remaining relative wage gains of home-based workers, which represent about two-thirds of the total gains, must be explained by changes in the distribution of home-based workers across occupation groups and changes in the home-based wage penalty *within* occupation groups. The table indicates that only 10% of these residual relative wage gains of home-based workers can be explained by changes in the occupational composition of home-based employment, with the other 90% accounted for by reductions in wage penalties on home-based jobs within occupations. In summary, the results in Tables 4 and 5 show that the rise in the home-based employment share and the decline in the home-based wage penalty in recent decades was observed not only in the aggregate but also quite generally within more narrowly defined occupation groups.

The evidence presented so far is consistent with the view that falling employer costs of offering home-based jobs, rather than rising worker valuations for home-based jobs, have been the primary source of growth in the home-based employment share in the last twenty years. What caused this decline in costs? Advances in IT are one obvious possibility. Several recent studies have provided evidence suggesting that innovations in IT may have played an important role in recent decades in 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 by firms (Bresnahan, Brynjolfsson, and Hitt 2002).

It seems likely that these IT advances would have raised the relative productivity of home-based workers, and thereby reduced employers' costs of offering home-based work arrangements, by more in some occupations (e.g., managers and business specialists) than in others (e.g., food or cleaning service). Thus, if IT advances were the main reason that employers' costs of offering home-based jobs fell and if the supply elasticity into home-based employment is similar across occupations, then one would expect that the occupations that experienced the largest increases in the home-based share of employment also had the largest gains in the home-based relative wage (i.e., largest declines in the home-based wage penalty). Moreover, since IT use rises with education (Autor, Katz, and Krueger 1998), one might additionally expect the largest gains in the home-based employment share and home-based relative wage to have occurred in occupations with high average education.

Figure 1 illustrates the relationship between changes in home-based relative wages and changes in home-based employment shares across the 20 occupation groups for the 1980-1990 and 1990-2000 periods. Home-based relative wages and home-based employment shares are measured in levels (logs) in the two graphs on the left (right) side of the figure. The size of each data point in the scatter plots is proportional to the average fraction of total employment accounted for by the corresponding occupation in the two relevant census years. Occupations in which the percentage of college graduates is at least 1.5 times as large as the percentage of college graduates in the full sample are identified as "high education occupations".

Most of the data points lie in the positive quadrant of each graph, indicating that both the home-based employment share and the home-based relative wage increased between census years in most occupations. However, the correlation between changes in the home-based employment share and changes in the home-based relative wage across occupations differs between decades. In the 1980-1990 period, occupations that saw larger increases in the home-based employment share appear to have seen smaller gains in the home-based relative wage.[17] In contrast, between 1990 and 2000, the change in the home-based employment share and the change in the home-based wage penalty are positively correlated across occupations.[18] In addition, above average gains in the home-based relative wage appear to have been concentrated in "high education occupations" only in the latter decade. Overall, the evidence in the figure would seem to suggest that IT innovation played a more prominent role in the growth in home-based wage and salary employment between 1990 and 2000 than for the similar growth that occurred in the preceding decade.

[17] The weighted regression line for 1980-1990 level changes in the upper left graph of Figure 1 has a slope coefficient of −8.743 with a standard error of 6.430. The weighted regression line for the 1980-1990 log changes in the upper right graph of Figure 1 has a slope coefficient of −.302 with a standard error of .069. The weights are equal to the product of occupational employment in the two relevant census years divided by the sum of occupational employment in the two relevant census years.

[18] The weighted regression line for 1990-2000 level changes in the lower left graph of Figure 1 has a slope coefficient of 5.740 with a standard error of 2.425. The weighted regression line for the 1980-1990 log changes in the lower right graph of Figure 1 has a slope coefficient of .067 with a standard error of .041. The weights are the same as described in footnote 17.

VI. On-the-Job Computer Use and the Home-Based Wage Penalty

One limitation of the evidence in Figure 1 is that the supply elasticity of workers into home-based jobs may vary across occupations, in which case changes in the home-based employment share and changes in the home-based wage penalty need not be positively correlated, even if these changes are caused by IT-induced changes in employer costs of offering home-based work arrangements that vary across occupations. Thus, additional evidence on the link between IT use and the home-based wage penalty would be useful. Fortunately, information on computer use at work has been collected on an occasional basis in supplements to the CPS since 1984. Probit models for on-the-job computer use can be estimated with these data and the resulting coefficient estimates can be used to impute predicted probabilities of computer use at work for observations in the census samples. This allows an examination of how the home-based wage penalty has varied with (the predicted probability of) on-the-job computer use.

Table 6, which updates Table 4 from Autor, Katz, and Krueger (1998), reports the proportions of wage and salary workers aged 25-64 who report using a computer at work in the October 1984, October 1993, and September 2001 CPS. I utilize these particular CPS supplements because they roughly correspond to the ten year intervals in the census data. There exist large differences in the incidence of on-the-job computer use across race, gender, education, and occupation categories in each year. While the proportion of workers using computers at work has risen substantially over time in all demographic and skill categories, the pattern of differences in on-the-job computer use across categories has remained stable over time.

Table 7 presents results from probit estimates of the determinants of computer use at work in 1984, 1993, and 2001. The covariates are nearly identical to those used in the log wage regressions in Table 3; the only variables not available in the CPS are indicators for whether the individual is a part-year worker, whether the individual is a home-based worker, and (in 1984 and 1993) whether the individual has a disability. The upper portion of the table reports marginal effects for selected covariates. The signs of the marginal effects are as expected given the raw proportions shown in Table 6 and are stable across survey years. However, the magnitudes of the marginal effects imply that differences in on-the-job computer use by race, education, and occupation have increased with the passage of time, as on-the-job computer use became more common.

The probit coefficients can be used to calculate a predicted probability of computer use at work for each individual in each CPS sample, and the lower portion of Table 7 reports summary statistics on these predicted probabilities. Several points are worth noting. First, in each year, the predicted probability of computer use at work varies greatly with observable individual characteristics. Second, occupational affiliation is an especially important predictor of on-the-job computer use, accounting for at least 80% of the variance in predicted probabilities of computer use at work in each year. Even so, the variation in predicted probabilities of on-the-job computer use within occupation groups is non-trivial. Finally, increases over time in (the predicted probability of) computer use at work appear to have occurred throughout the skill distribution.

Since the census samples include all of the variables that were used as covariates in the probit models for on-the-job computer use, the probit estimates for the 1984, 1993, and 2001 CPS samples also can be used to impute person-specific predicted probabilities of on-the-job computer use for the observations in the 1980, 1990, and 2000 census samples, respectively. I do not report summary statistics for these predicted probabilities, as they are virtually identical to those reported in Table 7. Of course, these predicted probabilities slightly overstate the true probabilities of on-the-job computer use for all observations in each *census year*, since each CPS sample was obtained a few years later than the corresponding census sample. However, given the apparent stability over time in the correlates of on-the-job computer use, this should have little effect on the pattern of variation in the predicted probabilities across individuals *within* each census sample.[19]

Having imputed a predicted probability of on-the-job computer use for each census observation, I estimate log wage equations of the form

$$\ln W_{it} = X_{it}\beta_t + \sum_{j=1}^{19}\gamma_{jt}D_{ijt} + \delta_t H_{it} + \lambda_t \hat{P}_{it} + \eta_t \hat{P}_{it} H_{it} + \varepsilon_{it}, \tag{7}$$

and

$$\ln W_{it} = X_{it}\beta_t + \sum_{j=1}^{19}\gamma_{jt}D_{ijt} + \sum_{j=1}^{20}\delta_{jt}D_{ijt}H_{it} + \lambda_t \hat{P}_{it} + \eta_t \hat{P}_{it} H_{it} + \varepsilon_{it}, \tag{8}$$

for each census year, where $\hat{P}_{it}$ is the predicted probability of on-the-job computer use for individual i in year t and all other variables are as defined in (1) and (2). These equations extend the specifications in (1) and (2) by allowing the home-based wage penalty to vary with an individual's predicted probability of using a computer at work. If advances in IT have had an important impact on the relative productivity of working at home, changes

[19] Indeed, there is an extremely high correlation between the three alternative predicted probability of computer use at work measures derived from the 1984, 1993, and 2001 CPS estimates, respectively. The correlation between the measures computed using the 1984 and 1993 estimates ranges between .95 and .96, depending on the census year. Similarly, the correlation between the measures computed using the 1993 and 2001 estimates is .97 in all census years. Even when the predicted probability measures are computed using the estimates from 1984 and 2001, which are separated by 17 years, the correlation ranges between .88 and .91, depending on the census year.

over time in the home-based wage penalty are likely to have differed among workers who vary in their (predicted probabilities of) computer use at work. The specification in (7) restricts the home-based wage penalty to be identical across occupations, except for differences associated with differences across occupations in the probability of on-the-job computer use. In contrast, the specification in (8) allows for occupational differences in the home-based wage penalty unrelated to the use of computers at work.

Table 8 reports the estimated coefficients on the home-based work variables in (7) and (8) for the 1980, 1990, and 2000 census samples, with the odd-numbered columns showing estimates of δ_t and η_t from (7) and the even-numbered columns showing estimates of η_t from (8). Since the hypothesis that home-based wage penalties are the same across occupations is rejected overwhelmingly in each census year, I focus on the estimates in the even-numbered columns. In 1980, there was no relationship between the home-based wage penalty and the probability of on-the-job computer use, after accounting for occupational differences in the home-based wage penalty. One decade later, workers with higher probabilities of using a computer at work faced larger within-occupation home-based wage penalties, other things equal. However, by the year 2000, the pattern had reversed and the within-occupation home-based wage penalty was smaller for individuals with higher probabilities of on-the-job computer use. Since home-based wage penalties were falling on average throughout the 1980-2000 period, a concise summary of the results is that home-based wage penalties decreased most for workers with the *lowest* probabilities of on-the-job computer use between 1980 and 1990 but decreased most for workers with the *highest* probabilities of on-the-job computer use between 1990 and 2000.

The recent history of IT innovation offers a plausible explanation for both the direction and timing of these changes in the relationship between the home-based wage penalty and the probability of computer use at work. The personal computer (PC) era began with the introduction of the Apple II in 1977 and the IBM PC in 1981. VisiCalc, the first spreadsheet software, was released in 1978. The 1980's brought faster microprocessors, new business software, dramatic declines in the real price of computing, and vast expansion of the installed computer base. These innovations likely altered job tasks and increased productivity more for workers with skills that were complementary to computers than for those without such skills.[20] However, given the frontiers of IT in 1990, few of the gains in on-site worker productivity resulting from increased computerization could have been realized in a home-based work setting. Thus, any reduction in home-based wage penalties between 1980 and 1990 likely would have been *smaller* among workers with the higher probabilities of using a computer at work, consistent with the empirical evidence in Table 8.

In the 1990's, progress continued on the same margins as in the 1980's but, importantly, breakthroughs occurred on new fronts as well. In particular, hypertext language was invented, and the World Wide Web was born, in 1990. The next few years saw the arrival of the first commercial web browsers and internet service providers, and with these came a massive expansion of file sharing.[21] These latter innovations, together with continued quality improvements and price declines for computer hardware, allowed individuals who used computers intensively in their work to perform many more of their

[20] Autor, Levy, and Murnane (2003) derive this implication in a formal model of the effects of computers on the task composition of jobs.
[21] Several sources report that traffic on the World Wide Web increased by over 300,000% in 1993. See, for example, Hobbes' Internet Timeline at http://www.zakon.org.

job tasks at home than was previously possible. These same advances likely had much less impact on home-based productivity for workers who did not use computers on the job. Thus, these observations suggest that any reduction in the home-based wage penalties between 1980 and 1990 would have been *larger* among workers with the higher probabilities of using a computer at work, again consistent with the findings in Table 8.

VII. Conclusion

This paper has used earnings data from the 1980, 1990, and 2000 U.S. Censuses of Population, supplemented with data on computer use at work from the 1984, 1993, and 2001 CPS, to analyze the changes in the home-based employment share and home-based wage penalty for prime-age, civilian wage and salary workers over the last two decades. The main findings are: (1) home-based employment grew much faster than on-site employment between 1980 and 2000; (2) the relative wage of home-based workers rose dramatically over this same period; (3) approximately one-third of the relative wage gains of home-based workers can be attributed to relative gains in observed human capital, with most of the remainder explained by reductions in the wage penalty on home-based jobs; (4) home-based employment shares rose and home-based wage penalties fell within almost all occupation groups and changes in the occupational composition of employment account for little of the aggregate changes; and (5) between 1980 and 1990, home-based wage penalties fell most for workers who were least likely to use a computer at work but, between 1990 and 2000, home-based wage penalties fell most for workers who were most likely to use a computer on the job.

Overall, these findings suggest that widespread decreases in employers' costs of offering home-based work arrangements were the key factor behind the growth in home-based wage and salary employment over the last several decades. The exact source of these general reductions in the cost of locating jobs at home is unclear. Possibilities include changes in production processes, organizational hierarchies, or compensation methods — which in turn may have been endogenous responses to technological change — that reduced employers' costs of monitoring work performed outside the office or reduced the costs to employers of physical separation between co-workers. At the same time, the variation in the timing and size of reductions in the home-based wage penalty across workers who differ in their likelihood of using a computer on the job is consistent with the view that advances in IT in the last several decades have had important direct impacts on the labor market productivity of both on-site and home-based workers.

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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	.0221	.0282	.0327	27.6	16.0	48.0
Wage and salary	64,098	82,428	93,185	28.6	13.1	45.4
On site	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	.0075	.0098	.0144	30.3	47.9	92.7
Self-employment	7,421	9,515	11,033	28.2	16.0	48.7
On site	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	.1487	.1878	.1872	26.3	–0.3	25.9

Note: Data come from the 5% 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% 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.

Table 2: Means and standard deviations of key variables for wage and salary workers aged 25-64, by year and home-based status						
	1980		1990		2000	
	On-site workers	At-home workers	On-site workers	At-home workers	On-site workers	At-home workers
Log of real hourly wage	2.68	2.26	2.65	2.41	2.68	2.72
(in 1999 dollars)	(.63)	(.87)	(.62)	(.81)	(.64)	(.81)
Female	.425	.571	.469	.556	.478	.541
Married	.723	.692	.658	.667	.631	.693
Black	.103	.046	.104	.049	.105	.054
Hispanic	.055	.055	.073	.078	.098	.071
Part-time worker	.121	.313	.126	.292	.117	.221
Part-year worker	.218	.302	.193	.258	.167	.182
Disabled	.040	.076	.035	.064	.104	.094
Potential experience	21.80	23.53	20.48	22.82	21.57	22.78
(in years)	(12.17)	(12.89)	(10.84)	(11.53)	(10.42)	(10.53)
Less than high school	.213	.225	.108	.125	.082	.063
High school degree	.379	.351	.333	.289	.297	.212
Some college	.185	.184	.298	.275	.310	.296
College degree or above	.223	.240	.261	.311	.311	.429
Managerial, business	.118	.158	.138	.171	.138	.211
Engineers, scientists	.032	.013	.035	.022	.042	.055
Healthcare practitioners	.026	.008	.033	.011	.037	.015
Teachers, educators	.063	.030	.062	.030	.059	.026
Arts, media, social service	.019	.076	.025	.090	.033	.068
Lawyers, judges	.004	.003	.006	.002	.006	.005
Technicians	.034	.015	.042	.019	.044	.039
Sales supervisors & reps	.043	.062	.057	.095	.049	.100
Retail sales	.038	.044	.038	.042	.042	.069
Office support	.110	.147	.098	.130	.107	.113
Mail & shipping clerks	.072	.039	.076	.044	.067	.049
Protective service	.018	.006	.020	.006	.023	.008
Food or cleaning service	.061	.069	.061	.073	.065	.036
Health or personal service	.031	.125	.031	.078	.035	.094
Farming, forestry, fishing	.011	.081	.013	.062	.007	.016
Mechanics & repairers	.040	.012	.037	.017	.040	.018
Construction trades	.038	.017	.038	.016	.051	.019
Extractive, precision prod	.052	.019	.039	.017	.031	.011
Machine operators	.105	.039	.075	.034	.065	.026
Vehicle operators	.085	.037	.078	.038	.058	.022
Observations (unweighted)	64,041	21,299	113,104	37,822	137,722	63,905

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 in this and all subsequent tables. The reported means and standard deviations 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. Standard deviations are shown in parentheses only for non-binary variables. 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 3: Log wage regressions for wage and salary workers aged 25-64, allowing for a homogeneous wage penalty for home-based work			
	1980	1990	2000
Potential experience	.0269	.0271	.0247
	(.0012)	(.0011)	(.0011)
(Square of potential experience)/100	−.0435	−.0409	−.0390
	(.0025)	(.0024)	(.0024)
Less than a high school degree	−.1101	−.1607	−.1491
	(.0095)	(.0110)	(.0118)
Some college	.0790	.1164	.1320
	(.0086)	(.0073)	(.0072)
College degree or above	.2765	.3747	.3855
	(.0106)	(.0096)	(.0095)
Black	−.0247	−.0301	−.0283
	(.0116)	(.0107)	(.0097)
Hispanic	−.0617	−.0650	−.0862
	(.0139)	(.0126)	(.0105)
Female	−.2021	−.1181	−.0953
	(.0127)	(.0109)	(.0101)
Married	.1194	.1480	.1520
	(.0113)	(.0102)	(.0097)
Married×Female	−.1617	−.1852	−.1583
	(.0150)	(.0137)	(.0125)
Number of kids	.0137	.0066	.0119
	(.0034)	(.0039)	(.0039)
Number of kids×Female	−.0512	−.0319	−.0248
	(.0050)	(.0054)	(.0053)
Disabled	−.1424	−.1266	−.0488
	(.0179)	(.0181)	(.0095)
Home-based worker	−.3098	−.1741	−.0078
	(.0079)	(.0064)	(.0051)
R^2	.2948	.3247	.3121
Number of observations (unweighted)	85,340	150,926	201,627

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 7 industries, 19 occupations, part-time work status, and part-year work status.

Table 4: Actual home-based employment shares and estimated home-based wage penalties for 20 occupation categories, 1980-2000

	Home-based employment share			Home-based wage penalty		
Occupation category	1980	1990	2000	1980	1990	2000
Managerial, business	.0091	.0113	.0214	−.3854	−.2654	−.0148
Engineers, scientists	.0027	.0058	.0182	−.1725	−.0726	.1115
Healthcare practictioners	.0023	.0032	.0056	−.3082	−.2649	−.0966
Teachers, educators	.0033	.0044	.0062	−.3400	−.2755	−.0792
Arts, media, social service	.0263	.0316	.0284	−.5900	−.3854	−.2009
Lawyers, judges	.0041	.0037	.0112	−.4842	−.1902	−.0375
Technicians	.0031	.0041	.0124	−.2183	−.0227	.0579
Sales supervisors & reps	.0100	.0150	.0281	−.0503	.0466	.1457
Retail sales	.0079	.0102	.0229	−.0727	.0436	.2862
Office support	.0092	.0121	.0149	−.1267	−.0678	.0017
Mail & shipping clerks	.0037	.0053	.0103	−.0999	−.0825	.0494
Protective service	.0023	.0029	.0049	−.3659	−.1425	−.0106
Food or cleaning service	.0078	.0108	.0077	−.2528	−.1869	−.0896
Health or personal service	.0273	.0227	.0366	−.6437	−.2931	−.2081
Farming, forestry, fishing	.0496	.0430	.0344	−.3375	−.2035	−.0930
Mechanics & repairers	.0020	.0041	.0063	−.2254	−.2785	−.0929
Construction trades	.0031	.0040	.0052	−.1832	−.1164	−.1007
Extractive, precision prod	.0025	.0039	.0052	−.2918	−.2460	−.1238
Machine operators	.0025	.0042	.0058	−.2507	−.2340	−.0902
Vehicle operators	.0030	.0045	.0053	−.2201	−.1440	−.0467

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. These regressions also include all of the explanatory variables listed in Table 3.

Table 5: Decompositions of changes over time in (1) the home-based employment share and (2) the mean log wage differential between home-based workers and on-site workers

	1980-1990	1990-2000	1980-2000
Total change in home-based employment share	.0022	.0050	.0072
Portion explained by changes in the composition of wage and salary employment between 20 occupation categories	.0004	.0002	.0007
Portion explained by changes in the incidence of home-based employment within 20 occupation categories	.0018	.0048	.0065
Total change in mean log wage differential between home-based workers and on-site workers	.1871	.2825	.4696
Portion explained by changes in the gap in mean observed skills between home-based workers and on-site workers	.0601	.0993	.1479
Portion explained by changes in the returns to observed skills, given the average gap in observed skills	−.0096	.0166	.0186
Portion explained by changes in the composition of home-based employment between 20 occupation categories	.0141	.0183	.0318
Portion explained by changes in the wage penalties for home-based work within 20 occupation categories	.1224	.1484	.2714

Note: The 20 occupation categories are those listed in Table 2. The decomposition in the upper panel of the table uses the formula in equation of (3) of the paper. The decomposition in the lower panel of the table uses the formula in equation (6) of the paper.

Table 6: Proportion of workers in various categories who use a computer at work

	1984	1993	2001
All workers	.267	.482	.580
Male	.236	.426	.522
Female	.307	.545	.644
Black	.179	.360	.460
Non-Black	.278	.498	.597
Hispanic	.162	.284	.336
Non-Hispanic	.273	.500	.610
Less than high school	.054	.097	.159
Exactly a high school degree	.206	.361	.417
Some college	.343	.567	.616
College degree or above	.431	.702	.838
Managers, business specialists	.467	.761	.844
Engineers, scientists	.599	.860	.918
Healthcare practitioners	.275	.576	.744
Teachers, educators	.336	.559	.788
Arts, entertainment, media, social service, religion	.258	.612	.781
Lawyers, judges	.295	.679	.931
Technicians	.504	.683	.753
Sales supervisors & representatives	.354	.650	.778
Retail sales	.137	.336	.433
Office support, records processing	.507	.824	.832
Mail, shipping, & communications clerks	.423	.678	.681
Protective service	.219	.449	.557
Food or cleaning service	.027	.080	.155
Health or personal service	.056	.152	.277
Farming, forestry, fishing	.015	.052	.175
Mechanics & repairers	.159	.319	.440
Construction trades	.042	.077	.150
Extractive, precision production	.158	.338	.397
Machine operators, assemblers	.075	.182	.261
Vehicle operators, handlers, equipment cleaners	.039	.134	.175

Note: The samples are limited to individuals aged 25-64 who were employed in a paid civilian job in the previous week (either working or with a job but not at work). The probabilities reported in the table are calculated using the CPS sampling weights. The unweighted sample sizes are 44,148, 46,225, and 51,200 for 1984, 1993, and 2001, respectively.

Table 7: Estimated marginal effects from probit estimates of the determinants of computer use at work

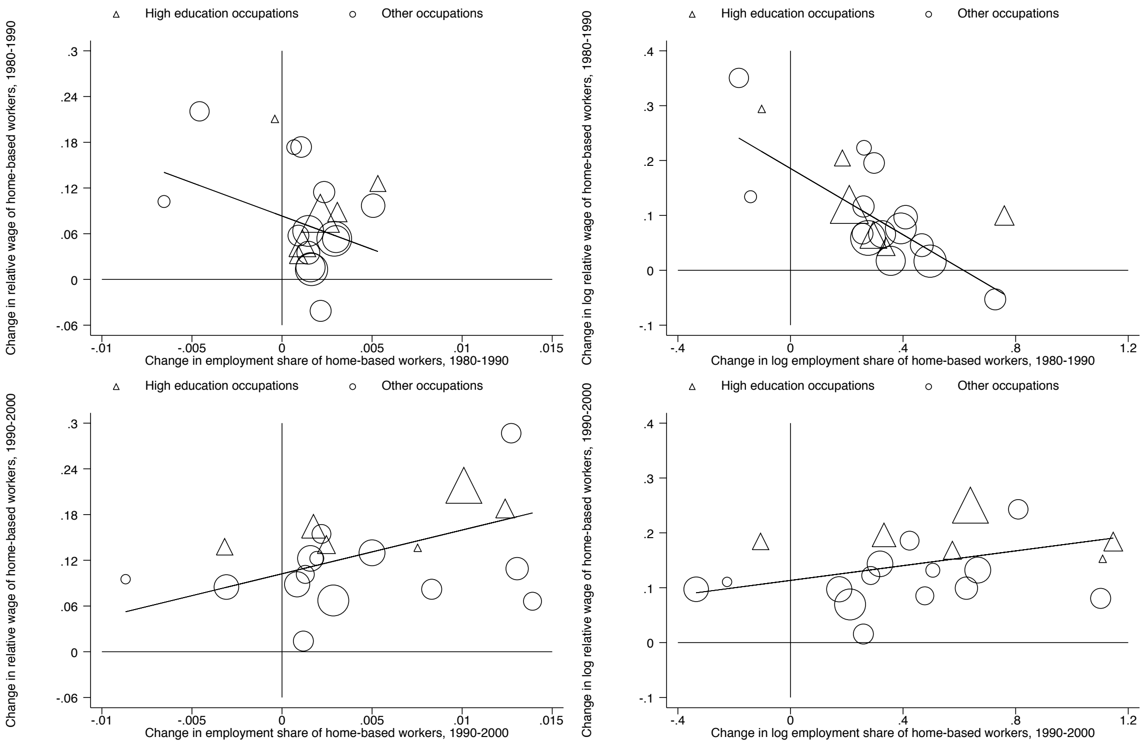
	1984	1993	2001
Less than a high school degree	−.0857	−.1838	−.1434
	(.0079)	(.0126)	(.0128)
Some college	.0661	.1181	.1040
	(.0068)	(.0078)	(.0070)
College degree or above	.0978	.1757	.2470
	(.0080)	(.0094)	(.0078)
Black	−.0480	−.0898	−.1104
	(.0073)	(.0102)	(.0100)
Hispanic	−.0348	−.0777	−.1270
	(.0100)	(.0124)	(.0105)
Female	.0515	.0683	.0699
	(.0090)	(.0120)	(.0104)
Married	.0193	.0683	.0351
	(.0080)	(.0117)	(.0097)
Married×Female	−.0280	−.0369	−.0157
	(.0102)	(.0151)	(.0129)
Number of kids	−.0007	−.0054	−.0063
	(.0031)	(.0040)	(.0043)
Number of kids×Female	−.0045	−.0013	−.0014
	(.0044)	(.0055)	(.0058)
P-value for joint significance of occupation dummies	<.0001	<.0001	<.0001
Summary statistics on predicted probability of computer use at work			
Mean	.267	.482	.580
Standard Deviation	.211	.295	.298
10^{th} percentile	.021	.067	.130
90^{th} percentile	.575	.853	.916
Within occupation standard deviation	.091	.100	.132

Note: The sample selection criteria and sample sizes are as described in Table 6. The estimates use the CPS sampling weights and heteroskedasticity-robust standard errors for the estimated marginal effects are shown in parentheses. The dependent variable is an indicator that equals 1 if the individual directly uses a computer on the job. All specifications also include potential years of experience and its square and dummies for 7 industries, 19 occupations, part-time work status, and (for the 2001 sample) disability status as explanatory variables.

Table 8: Relationship between predicted probability of computer use and home-based wage penalty, for wage and salary workers aged 25-64

	1980		1990		2000	
	(1)	(2)	(3)	(4)	(5)	(6)
Home-based worker	−.3841 (.0123)		−.2102 (.0117)		−.1373 (.0122)	
Home-based worker × predicted probability of computer use at work	.3218 (.0347)	.0480 (.0622)	.0750 (.0193)	−.1019 (.0485)	.1952 (.0169)	.1615 (.0405)
Home-based worker × occupation dummies included?	No	Yes	No	Yes	No	Yes
P-value on test of equality of home-based worker × occupation coefficients		<.0001		<.0001		<.0001
R^2	.2949	.2954	.3248	.3252	.3122	.3127

Note: The results in columns (1), (3), and (5) come from regressions identical to those reported in Table 3 except that each individual's predicted probability of using a computer at work and the interaction of this predicted probability with an indicator for having a home-based job are included as additional regressors. The results in columns (2), (4), and (6) come from regressions identical to those reported in Table 4 except that the predicted probability of using a computer at work and the interaction of this predicted probability with an indicator for having a home-based job again are included as additional regressors. The predicted probabilities of using a computer at work for individuals in the 1980, 1990, and 2000 census are constructed using, respectively, the probit results from the 1984, 1993, and 2001 CPS samples reported in Table 7. The estimates use the adjusted census sampling weights and heteroskedasticity-robust standard errors are shown in parentheses.


High education occupations
Other occupations
Change in relative wage of home-based workers, 1980-1990
Change in employment share of home-based workers, 1980-1990
Change in log relative wage of home-based workers, 1980-1990
Change in log employment share of home-based workers, 1980-1990
Change in relative wage of home-based workers, 1990-2000
Change in employment share of home-based workers, 1990-2000
Change in log relative wage of home-based workers, 1990-2000
Change in log employment share of home-based workers, 1990-2000
-.06
0
.06
.12
.18
.24
.3
-.01
-.005
0
.005
.01
.015
-.1
0
.1
.2
.3
.4
-.4
0
.4
.8
1.2