Dissecting wage dispersion.

CANNON, S. and MUSTRE-DEL-RIO, J.

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Dissecting Wage Dispersion

By San Cannon and José Mustre-del-Río

At any time, wages differ dramatically across U.S. workers. Some differences in workers' hourly wages may be due to differences in observable characteristics such as age, sex, race, or education level. But substantial dispersion in wages across individuals persists after accounting for these differences. This wage dispersion prompts a range of questions. What is the source of this dispersion and does it matter where it comes from? Are hourly wages more dispersed today than in the past?

In this article, we investigate the sources of wage dispersion for different demographic groups as well as how these sources have changed over time. To do so, we decompose residual wage dispersion—the variation in wages that is unexplained by standard demographic characteristics—to discover how much of the dispersion is due to "who you are" (also known as the permanent component) versus "where you work" (also known as the match-specific component).

Our analysis of individual-level data from the Survey of Income and Program Participation (SIPP) suggests that the match-specific component is responsible for a substantial fraction of residual wage differences across individuals. Upon switching jobs, some individuals land more lucrative matches, while others earn less for the same work. We also find that residual wage dispersion is similar across sexes and education levels.

San Cannon is an assistant vice president and economist at the Federal Reserve Bank of Kansas City. José Mustre-del-Río is an economist at the bank. This article is on the bank's website at www.KansasCityFed.org.

Section I describes wage dispersion and its stability over time. Section II introduces a simple model to dissect wage dispersion into its components. Section III shows that the match-specific component is larger than the permanent component for both men and women. Section IV investigates differences across educational groups and finds that men and women with the same education level display similar sources of wage dispersion; more generally, the sources of wage dispersion within sexes but across educational groups are also similar.

I.   Describing Wage Dispersion

Headline compensation measures, such as an average salary or median income, mask potentially large differences between individual workers' wages. To get a sense of these differences, we look at statistics that measure the degree of variation, or dispersion, in individual wages relative to their average. Chart 1 illustrates this dispersion relative to the mean: the blue line represents real average hourly wages from 1996 to 2013, while the shaded area represents one standard deviation above and below that mean. In general, a narrow shaded area suggests wages are concentrated near the mean, while a wide area suggests wages are quite disperse.

Over the last decade, U.S. workers' hourly wages have been fairly disperse. The blue line in Chart 1 shows real average hourly wages ranged from a low of $12.22 in 1996 to a high of $15.39 in 2008, but the values one standard deviation from the mean ranged from $10.63 to $16.95. As noted, differences in observable characteristics like age, sex, race, or education can widen this range. However, these observables characteristics tend to explain only a minor portion of wage differences across individuals.[1]

Chart 1 also reveals that the dispersion of wages has remained fairly stable over the last decade. For example, the dispersion was only 4.4 percent wider in 1996, the year with the highest dispersion, than it was in 1999, the year with the lowest measured dispersion. Whether the underlying sources of this apparent stability have changed over time, however, remains an empirical question.

To answer this question, we use data from the SIPP, a household-based survey designed as a continuous series of national panels. Each panel features a nationally representative sample of 14,000 to 52,000

Chart 1
Mean and Standard Deviation of Real Wages over Time

Mean real wage
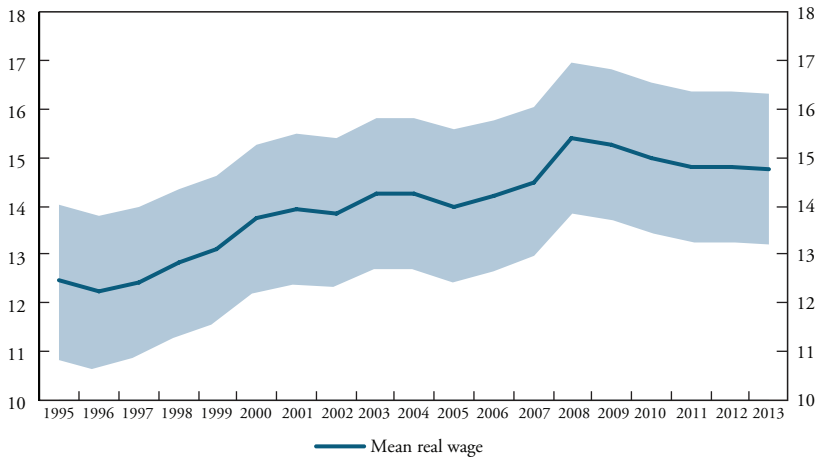
Note: Shaded area represents +/– one standard deviation from the mean.
Sources: Survey of Income and Program Participation (SIPP) and authors' calculations.

households interviewed once every four months over four years.[2] Respondents are asked retrospective questions about the previous four months, allowing us to construct monthly histories. The survey includes questions related to various types of income, labor force participation, social program participation and eligibility, and general demographic characteristics. All household members who are interviewed during the first round of interviews are tracked for the entire panel, even if they move.[3] In addition, new individuals can enter the sample after the first wave if they become part of a participating household. We use data at the individual level for as long as an individual is in the sample.

Table 1 describes the survey coverage for the panels we use in our analysis. In particular, we use the 1996, 2001, 2004, and 2008 panels of the SIPP, which roughly cover the 1996–2000, 2001–03, 2004–07, and 2008–13 time periods. We limit the data set to people age 22 to 61 who are employed for at least three weeks in a month. We exclude individuals who are never observed working during the survey as well as those who never switch jobs. When individuals report more than one employer during a month, we use the job characteristics and hourly wages associated with their main job, which we define as the job for which they work the most hours during the week. We record the basic

Table 1
Survey Coverage of SIPP Data

Panel	Waves	Months	Interview dates	Individuals
1996	12	48	Apr. 1996–Mar. 2000	95,315
2001	9	36	Feb. 2001–Jan. 2004	90,408
2004	12	48	Feb. 2004–Jan. 2008	110,659
2008	16	64	Sep. 2008–Dec. 2013	105,663

Sources: SIPP and authors' calculations.

demographics, labor force status, employer characteristics, and pre-tax hourly wages—our measure of labor income—for all workers in our sample. For workers who are not paid at an hourly rate, we impute one based on their monthly earnings, weeks worked per month, and hours worked per week.[4] Lastly, we also define two broad categories for education level: "higher education" describes workers who have at least some college experience, while "lower education" describes workers who have at most a high school diploma.

Table 2 shows the characteristics of the resulting data set for Males and Females based on respondents' answers to the question about their sex. While several trends are common for both male and female workers, their experiences differ in a few notable ways.

First, female workers are systematically less likely to be employed than male workers. In the 1996 panel, for example, over 77 percent of males were employed compared with 70 percent of females. Over time, this gap has narrowed: in the 2008 panel, roughly 69 percent of males were employed compared with 67 percent of females.

Second, female workers are also systematically less likely to switch jobs than male workers. Indeed, at its peak during the 2004 panel, the job-switching rate—the percentage of workers in a particular month who have a different employer than the previous month—is 3.1 percent for males compared with 2.9 percent for females.

Third, the proportion of female workers with higher education increases more over time than the proportion of male workers. Specifically, the proportion of higher-educated females rises 17 percentage points from the 1996 panel to the 2008 panel compared with 11 points for males.

Table 2
Sample Characteristics

Panel A: Male Respondents

Variable	1996 Mean	2001 Mean	2004 Mean	2008 Mean
Age	36.37	37.89	38.09	38.87
Race (percent white)	85.81	84.53	82.18	82.67
Married (percent)	69.62	68.82	67.08	66.96
Higher education (percent)	55.36	56.28	62.37	64.41
Job switch rate (percent)	2.87	2.71	3.09	2.14
Full time (percent)	89.81	89.83	90.51	90.21
Employed observations (percent)	77.25	75.26	71.93	69.46
Standard deviation log wage (w)	0.42	0.42	0.43	0.43
Individuals	4,616	3,321	5,445	7,443
Observations	179,798	100,373	177,851	347,618

Panel B: Female Respondents

Variable	1996 Mean	2001 Mean	2004 Mean	2008 Mean
Age	35.46	36.85	37.33	38.41
Race (percent white)	82.79	79.78	78.95	78.81
Married (percent)	65.40	60.13	60.75	61.31
High education (percent)	56.25	59.81	67.71	71.97
Job switch rate (percent)	2.80	2.55	2.93	2.00
Full time (percent)	69.13	69.47	72.80	73.91
Employed observations (percent)	69.96	69.84	68.59	67.48
Standard deviation log wage (w)	0.42	0.44	0.44	0.44
Individuals	6,028	3,984	6,305	8,165
Observations	242,522	120,725	211,973	381,343

Sources: SIPP and authors' calculations.

Accounting for male and female respondents' different propensities to work, switch jobs, and attain higher education is crucial in assessing the sources of wage dispersion. As a result, we perform these decompositions in Sections III and IV separately by sex.

II.   Differentiating Sources of Wage Dispersion

Following the work of Low, Meghir, and Pistaferri, we decompose residual wage dispersion into three components: permanent, matching or mobility, and transitory. The permanent component can be viewed as the variation in wages that results from lifetime differences across

individuals. Lifetime differences can include both external factors in the labor market, such as a structural shift in demand for certain skills, or individual factors, such as being particularly athletic, good with numbers, or chronically ill. Differences in this component have long-lasting effects on an individual's future wage path. One way to think about this component is as the component of residual wage variation due to "who you are."

The matching or mobility component reflects variation in residual wages attributable to an individual's specific employer. When individuals switch jobs, some land matches that pay more, while others land matches that pay less, even though both individuals may have similar observable characteristics and be working in the same industry and occupation. For example, individuals who are currently employed may be more picky when switching jobs and do so only when the pay is high enough; alternatively, currently unemployed workers may be more desperate for any job regardless of its pay.[5] Additionally, some individuals may switch jobs with the specific goal of higher pay, while others may switch jobs chasing different amenities (for example, location, hours, or flexibility). One way to think of this matching component is as the variation in residual wages due to "where you work."

Finally, the transitory component reflects short-term residual wage differences across individuals that do not accumulate and are not expected to greatly affect their future wage paths. These differences could reflect, for example, some individuals taking vacation or short-term leave or earning one-time bonuses. In practice, transitory shocks are mostly measurement error, and in our analysis, their variance is indeed small. While we do calculate the transitory component, we do not focus on it in the remaining analysis.

Again following Low, Meghir, and Pistaferri, we consider a parsimonious statistical framework to disentangle the underlying sources of wage differences across individuals observed in the U.S. economy. Specifically, we assume that wages in the data are governed by the following process:

$$ln\ w_{it} = x'_{it}\psi + u_{it} + e_{it} + a_{ij(t_0)}, \qquad (1)$$

where w_{it} is log real hourly wage for individual i at time t, $x'_{it}\psi$ is a collection of individual descriptors (such as sex, race, and education)

and time, u_{it} is the permanent component of wages, e_{it} is the transitory component, and $a_{ij(t_0)}$ is the match-specific component of wages for worker i at job j which began at time t_0 (potentially prior to today's date t). The notation on a reflects the assumption that the match-specific component is constant over the entire duration of the employment relationship. Thus, the only way this component will change over time is if the worker switches jobs.

Although Equation 1 includes all three sources of residual wage dispersion, we must make additional assumptions to statistically distinguish between them. We assume the transitory shock, e_{it}, to be 0 on average with a standard deviation of σ_e. Importantly, the e shock that worker i experiences at time t is not persistent—in other words, the shock only affects wages for time t and has no influence on future wages. Similarly, yesterday's shock has no influence on today's wages.

In contrast, the permanent component does exhibit persistence between periods. We model this process as following a random walk:

$$u_{it} = u_{it-1} + \varsigma_{it}.$$

That is, a worker's permanent component today depends on yesterday's realization plus some additional shock that we expect to be 0 on average with a standard deviation of σ_ς. We assume the shocks are independent across time and unrelated to the transitory shock: today's ς shock doesn't affect tomorrow's ς shock. Additionally, today's ς has no bearing on today's e shock. Importantly though, today's ς shock affects an individual's wages today, tomorrow, and throughout their productive careers, because these shocks accumulate through u_{it}. The events that occur in a single period will have effects that accumulate with other such productivity shocks over the course of an individual's working life.

The final component in our wage equation, the match-specific shock $a_{ij(t_0)}$, is also expected to be 0 on average with a standard deviation of σ_a. Recall that $a_{ij(t_0)}$ specifies the contribution to real wages based on worker i being matched to job j which began in period t_0. If worker i receives an offer in $t+1$ for a new job j' and accepts the offer, then the match component has a wage differential which contributes to the dispersion:

$$\xi_{it+1} = a_{ij'(t+1)} - a_{ij(t_0)}.$$

This term can be thought of as a "mobility premium." We assume workers only observe the realization of $a_{ij'(t+1)}$ upon switching jobs. Thus, sometimes ξ will be positive (denoting a wage increase), while other times ξ will be negative (denoting a wage loss).

Combining all these terms, we define the change in wages for individual i from t to $t-1$ as:

$$\Delta w_{it} = \Delta x'_{it} \psi + \varsigma_{it} + \Delta e_{it} + \xi_{it} M_{it}, \qquad (2)$$

where M_{it} is equal to 1 if person i has a new job at time t and 0 otherwise.

Because we are interested in estimating the variation in wages that is not explained by observable characteristics, we remove the $x'_{it} \psi$ term from the wage equation. To do so, we first need an unbiased estimate of ψ to net out the term $\Delta x'_{it} \psi$ from both sides of Equation 2. We employ standard econometric techniques to estimate ψ. In particular, we address the issues associated with only observing wages for those who choose to work and only observing job switches for those who choose to move.[6]

Netting out wage variation explained by observables results in the following expression relating residual wage variability to the three components of interest:

$$g_{it} = \varsigma_{it} + \Delta e_{it} + \xi_{it} M_{it}. \qquad (3)$$

Recall, the three components have variance measures σ_ς^2, σ_e^2, and σ_a^2, respectively. We turn next to the data used to estimate these parameters.

III. Documenting Wage Dispersion

To gain insight into the sources of wage variation across individuals, we apply the statistical decomposition outlined in the previous section to our SIPP panel data. To highlight how these sources have changed over time, we present results of the decomposition for each SIPP panel separately and for men and women separately. Our main results are shown in Table 3.

The first column of Table 3, which presents results from the 1996 panel, confirms some findings from prior research. Variation in the transitory component is small relative to the other components, suggesting temporary shocks only partly explain the dispersion of wages across individuals. In addition, variation in the permanent component is much larger, suggesting differences across individual workers

Table 3
Variation in Wages by Component

Standard deviation	1996		2001		2004		2008	
	Male	Female	Male	Female	Male	Female	Male	Female
Permanent (σ_ζ^2)	0.090 (0.003)	0.086 (0.003)	0.103 (0.007)	0.101 (0.005)	0.073 (0.006)	0.075 (0.003)	0.072 (0.003)	0.068 (0.004)
Transitory (σ_r^2)	0.048 (0.002)	0.043 (0.002)	0.042 (0.003)	0.043 (0.004)	0.02 (0.002)	0.027 (0.003)	0.027 (0.002)	0.023 (0.008)
Match-specific (σ_a^2)	0.285 (0.013)	0.276 (0.009)	0.304 (0.023)	0.327 (0.040)	0.260 (0.021)	0.271 (0.010)	0.302 (0.016)	0.297 (0.014)
Observations	283,489	337,374	137,802	149,655	229,240	260,627	471,344	504,281

Note: Numbers in parentheses are bootstrap standard errors based on 400 replications. Wages are measured in logs. Sources: SIPP and authors' calculations.

account for a greater share of wage dispersion. Lastly, variation in the match-specific is even larger, suggesting differences in where people work contribute most to wage differences across individuals.[7]

To give some quantitative interpretation to the numbers in the first column of Table 3, consider a man earning an hourly wage of $14.60 in a particular month, the sample average for men in 1996, whose match is of average quality (specifically, $a_{ij\,(t_0)} = 0$). If he receives a positive, one standard deviation shock to the transitory component of wages one month later, his earnings for that month only would increase to $15.30 or by 4.8 percent, less than a dollar increase per hour worked. In contrast, a one standard deviation shock to the permanent component of wages would increase his earnings permanently next month to about $15.90 or by 9 percent, over a dollar increase per hour worked. Finally, if he switches jobs and lands a match with quality one standard deviation above average, his earnings would see a one-time permanent increase (over the life of the match) to about $18.80 or by 28.5 percent, a more than four dollar increase per hour worked. Thus, from one month to the next, transitory shocks are practically negligible, shocks to the permanent component are more substantial, and shocks to the job-specific component are quite large.

A similar pattern holds for women: in 1996, the average real wage for women in our sample was $11.25. For a woman with an average job match, a one standard deviation transitory shock would result in an hourly wage of about $11.75, a 4.3 percent increase. A one standard deviation permanent shock would result in an hourly wage of about $12.25, an 8.6

percent increase. And a new job match one standard deviation higher in quality would result in an hourly wage of about $14.40, a nearly 28 percent or roughly three dollar per hour increase.

While the dollar figures illustrated above seem to imply significant differences across the sexes, the relative contributions of the permanent and match-specific components to wage dispersion are not statistically different for men and women in any of the panels. Chart 2 shows 95 percent confidence intervals around the permanent and match-specific component estimates for men and women derived from the bootstrap standard errors.[8] For each panel of the SIPP, the possible values of the point estimate have substantial overlap, illustrating similarity in the measure across the sexes. Even across the SIPP panels, there is little distinguishable variation between sexes. The estimates of the permanent component for both men and women are higher in the 2001 panel than in the other panels, but given the small sample size and large error bands, we do not attribute any significance to the difference.

Overall, shocks to the permanent component of wages account for a large fraction of differences in lifetime earnings across individuals regardless of sex, since these shocks accumulate over time. In contrast, differences in the match-specific component only persist as long as individuals stay in the same job and do not accumulate over time. Thus, which component is more relevant critically depends on the question at hand. For example, differences in the permanent component may be more important for understanding the implications of policies such as Social Security, which depend on lifetime earnings. Alternatively, differences in the match-specific component may be more germane for the design of short-term policies such as unemployment insurance.

IV. Differences in Wage Dispersion by Education Level

As education plays a large role in potential earnings, we might expect to see differences in wage dispersion across education levels. Highly educated individuals, for example, may have higher wage dispersion for several reasons: they may select into riskier occupations (for example, CEOs); they may work in a larger set of jobs; and they may be more averse to unemployment and thus less particular about which job they take. Low, Meghir, and Pistaferri's results show that the contributions of the components of wage dispersion differ modestly across
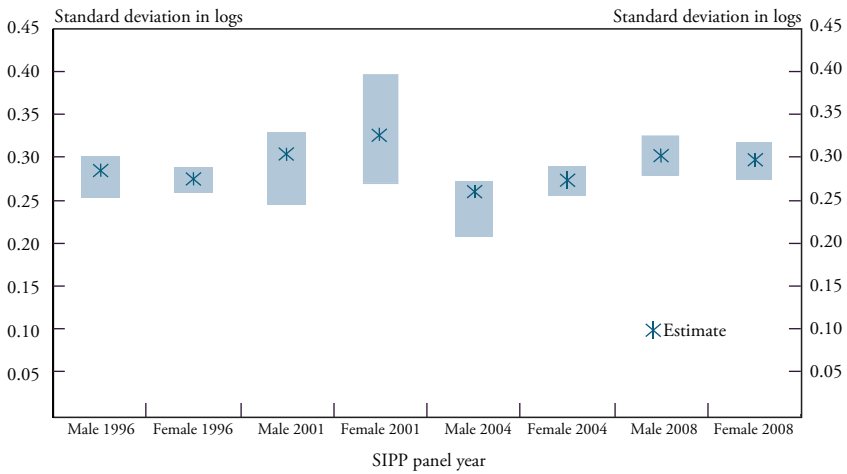
Chart 2

Estimates of Permanent and Match-Specific Components with Confidence Intervals

Panel A: Permanent Component
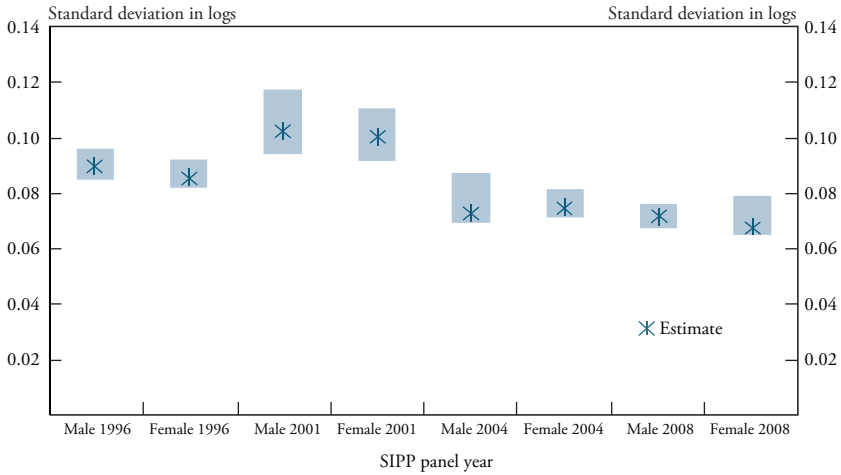
Panel B: Match-Specific Component

Note: Blue bars represent the 95 percent confidence interval constructed from the 400 bootstrapped replications.
Sources: SIPP and authors' calculations.

educational groups. Their results are similar to other research, most of which has focused solely on men (Meghir and Pistaferri; Carroll and Samwick). We investigate these effects for both male and female workers. Table 4 presents the decomposition results for the two educational groups broken down by sex.

Table 4 shows that male and female workers of the same education level have similar sources of wage dispersion. For example, in the 1996 panel, the standard deviation of the permanent component—who you are—is nearly identical for lower educated males and females (0.088 and 0.086, respectively). In addition, the standard deviation of the match-specific component—where you work—is not statistically different for lower educated males and females (0.264 and 0.247, respectively). The panels in Chart 3, which are based on the results from Table 4, show that the same conclusion holds when looking at higher educated males and females in 1996, or when looking at males and females of the same education level over time. Within each education level, the contributions of the components to wage dispersion do not appear to vary significantly by sex.

Likewise, differences in the sources of wage dispersion across educational categories (but within a particular sex) are not statistically significant, though they appear large. This finding is consistent with previous work (Low, Meghir, and Pistaferri; Carroll and Samwick). The panels in Chart 4 show the estimates and error bands for male and female workers across education groups. The match-specific component appears to differ by education in the 2001 panel for females and the 2004 and 2008 panels for males. However, formal hypothesis tests using our bootstrapped standard errors indicate that we cannot reject that the differences are significant at typical levels (specifically, at or below the 5 percent level).[9] More generally, these results help explain why the notable upward trend in female educational attainment did not affect the estimates from the previous section. Though female workers have increasingly become more educated, higher educated females have similar sources of wage dispersion to lower educated females.

Table 4
Variation in Wages by Education

Panel A: Lower Education

Standard deviation	1996		2001		2004		2008	
	Males	Females	Males	Females	Males	Females	Males	Females
Permanent (σ^2_ς)	0.088 (0.005)	0.086 (0.007)	0.105 (0.008)	0.094 (0.007)	0.071 (0.007)	0.069 (0.005)	0.067 (0.004)	0.069 (0.004)
Transitory (σ^2_ε)	0.040 (0.003)	0.033 (0.013)	0.030 (0.002)	0.035 (0.006)	0.019 (0.008)	0.019 (0.003)	0.012 (0.003)	0.014 (0.003)
Match-specific (σ^2_τ)	0.264 (0.016)	0.247 (0.017)	0.278 (0.023)	0.255 (0.021)	0.216 (0.028)	0.245 (0.014)	0.257 (0.022)	0.262 (0.023)
Observations	117,620	135,290	55,291	56,552	78,819	76,147	150,289	131,812

Panel B: Higher Education

Standard deviation	1996		2001		2004		2008	
	Males	Females	Males	Females	Males	Females	Males	Females
Permanent (σ^2_ς)	0.091 (0.004)	0.086 (0.003)	0.102 (0.010)	0.104 (0.008)	0.074 (0.005)	0.077 (0.003)	0.090 (0.004)	0.070 (0.006)
Transitory (σ^2_ε)	0.053 (0.003)	0.048 (0.002)	0.048 (0.012)	0.047 (0.005)	0.032 (0.006)	0.029 (0.004)	0.032 (0.002)	0.025 (0.014)
Match-specific (σ^2_τ)	0.302 (0.016)	0.294 (0.012)	0.325 (0.031)	0.364 (0.064)	0.282 (0.021)	0.281 (0.015)	0.323 (0.020)	0.309 (0.018)
Observations	165,869	202,084	81,881	93,103	150,421	184,480	321,055	372,469

Note: Numbers in parentheses are bootstrap standard errors based on 400 replications. Wages are measured in logs.
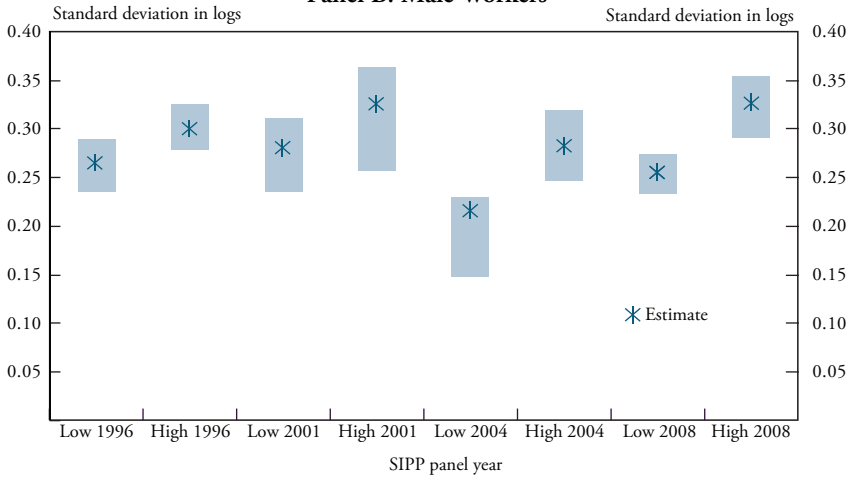Sources: SIPP and authors' calculations.

Chart 3
Estimates of Match-Specific Component for Workers by Education

Panel A: Lower Educated Workers

Standard deviation in logs   Standard deviation in logs

SIPP panel year

Panel B: Higher Educated Workers

Standard deviation in logs   Standard deviation in logs

SIPP panel year

Note: Blue bars represent the 95 percent confidence interval constructed from the 400 bootstrapped replications.
Sources: SIPP and authors' calculations.

Chart 4
Estimates of Match-Specific Component for Workers by Sex

Panel A: Female Workers
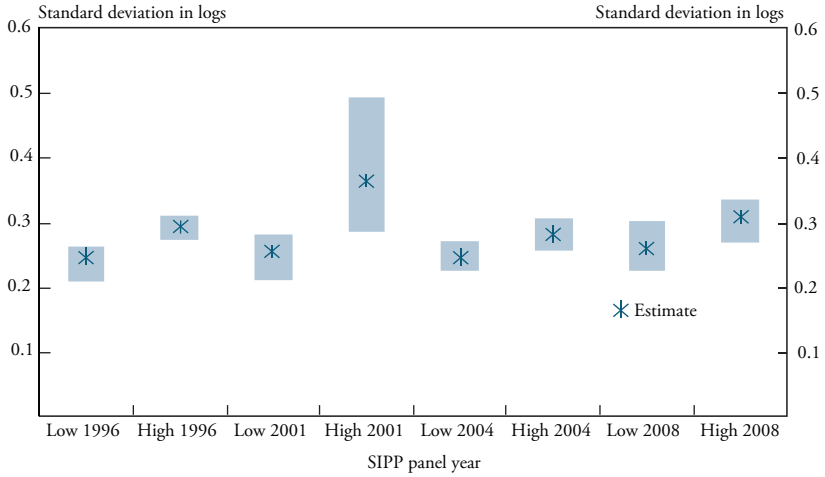
Panel B: Male Workers

Note: Blue bars represent the 95 percent confidence interval constructed from the 400 bootstrapped replications.
Sources: SIPP and authors' calculations.

V.   Conclusion

Wages are substantially dispersed across workers, jobs, and employers in the U.S. economy. Although some of that dispersion is due to demographic factors, we find that after controlling for those differences, both "who you are" (the permanent component of wage dispersion) and "where you work" (the match-specific component of wage dispersion) contribute to the range of wages paid. Distinguishing between the permanent and match-specific components is crucial from a policy perspective. If a great deal of residual wage differences across individuals are attributable to the long-lasting permanent component, policies may focus on early interventions prior to labor market entry, so that the benefits accrue over individuals' productive lifetimes. Alternatively, if residual wage differences are mostly attributable to the match-specific component, policies such as unemployment benefits may provide partial insurance.

Our calculations show that contribution of the match-specific component to dispersion is significantly larger than that of the permanent component. That said, we urge caution in interpreting larger to mean more important. Only 2 to 3 percent of the workforce switches jobs in any one month, so while the contribution of the match-specific component is substantial, its reach is limited. In addition, the effect of the match-specific component only lasts as long as a particular match. If workers change jobs again, then a new "mobility premium" will take effect. In contrast, the permanent component accumulates over the course of a worker's lifetime and, therefore, may be more relevant to the design of long-run policies rather than short-term social insurance measures.

Endnotes

[1]See, for example, Katz and Autor.

[2]Most panels are four years, but some are as short as two-and-a-half years. Prior to 1993, a new panel was introduced every year. The first four-year panel was introduced in 1996. The second four-year panel started in 2000 but was canceled after eight months due to budget restrictions. As a result, a shorter three-year panel was introduced in 2001.

[3]The survey does not track individuals if the move takes them out of the scope of the survey such as if they go overseas, into the military, or become institutionalized.

[4]More formally, we estimate a linear regression relating hourly wages to monthly earnings, weeks worked in a month, and hours worked per week using the sample of individuals who report all these measures. Then, we impute hourly wages for non-hourly workers using their recorded monthly earnings, weeks worked, and hours worked per week.

[5]More formally, on-the-job search is an important mechanism for generating residual wage dispersion as suggested by Horstein, Krusell, and Violante.

[6]We do two Heckman selection corrections to control for the decision to work and the decision to switch jobs. More specifically, following Low, Meghir, and Pistaferri, we estimate a Probit model relating employment status to observables ($P_{it} = z'_{it} \varphi + \pi_{it}$) and a separate Probit model relating observed job switching to observables ($P_{it} = k'_{it} \theta + \mu_{it}$). Note that the vectors of observables z_{it} and k_{it} are different from each other and from x_{it}. For example, we allow unearned income, spousal employment, and number of children present in the household to enter in z_{it} and k_{it} but not x_{it}. Lastly, the total number of job switches observed during the panel enters in k_{it} but not z_{it}.

[7]This latter finding on the importance of where you work is related to the recent work of Song and others. Using administrative data on U.S. workers' annual earnings, they find that nearly two-thirds of the rise in dispersion of annual earnings from 1978 to 2013 is due to differences in the firms where people work, while the remaining one-third cannot be explained by these differences.

[8]Bootstrapped standard errors are computed by replicating the estimation using 400 random samples (drawn with replacement) and computing the standard deviation of the resulting estimates.

[9]The p-value for the comparison of women across educational levels in 2001 is 0.104. For the men, the relative p-values are 0.127 in 2004 and 0.042 in 2008.

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