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Underpaid or Overpaid? Wage Analysis for Nurses Using Job and Worker Attributes

Barry T. Hirsch* and Edward J. Schumacher†

Nursing shortages are common despite the fact that nurses earn far higher wages than other college-educated women. Our analysis addresses the puzzle of "high" nursing wages. Employee data from the Current Population Survey are matched with detailed job descriptors from the Occupational Information Network. Nursing requires high levels of compensable skills and demanding working conditions. Standard log wage regression estimates indicate nursing wage advantages of about 40%. Accounting for job attributes reduces estimates to roughly 20%. Rather than transforming ordinary least squares log gaps to percentages, alternative methods measuring Mincerian gaps produce estimates of 15% or less. We conclude that nurses receive compensation that is much closer to opportunity costs than that seen in standard analyses, narrowing the shortage puzzle. Supply constraints in nurse licensing can produce wages above long-run opportunity costs but that are too low to clear short-run labor markets during periods of growing demand. The analysis provides broader implications for the conduct of wage analyses.

JEL Classification: I12, J31, J44

1. Introduction

Registered nurses (RNs) are widely believed to be in short supply, with hospitals having reported unfilled vacancies over sustained periods and shortfalls in future supplies of RNs widely predicted.[1] Sustained shortages of RNs present a puzzle. Shortages are seemingly inconsistent with a theory of competitive markets, wherein wages tend toward levels equating to labor demand and supply.[2] Low wages and shortages can exist in monopsonistic labor

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[1] See National Center for Health Workforce Analysis (2002); Spetz and Given (2003); and Aiken and Cheung (2008). Buerhaus, Auerbach, and Staiger (2009) show there have been recent increases in nursing supply and that shortages have eased, but they argue forcefully that they will return.

[2] Our discussion applies to "economic" shortages, which exist when there is excess demand (vacancies) at the current wage level or, in a dynamic setting, labor demand increasing faster than supply and wages slow to adjust. The nursing human resource literature often focuses on "need-based" or "professional standards" shortages, in which the available number of RNs is less than the number regarded as necessary to properly serve a given market (see Folland, Goodman, and Stano 2007, pp. 338–44; Goldfarb, Goldfarb, and Long 2008).

markets, yet evidence supporting nursing monopsony is neither abundant nor compelling (e.g., Hirsch and Schumacher 2005). Moreover, wage analyses indicate that RN relative wages have increased markedly over time and are well in excess of the wages received by other college-educated women. Based on wage analyses, an argument can be made that RNs are "overpaid." Based on evidence of shortages, an argument can be made that RNs are on average "underpaid." Less evident is how both views can be correct.

In this study we address the nursing wage-employment puzzle and attempt to answer the following question: Are nurses paid wages below, above, or equal to long-run opportunity costs? We combine Current Population Survey (CPS) data containing information on individual RN and non-RN wages and attributes with data providing a rich set of job content descriptors measuring occupational skills and working conditions. The job descriptors, taken from the Occupation Information Network (O*NET), show that nursing jobs require relatively high levels of skill and have demanding working conditions. Incorporating the O*NET job content measures into the CPS analysis sharply reduces estimates of relative RN wages. A shift from ordinary least squares (OLS) Mincerian log wage gap estimates to alternative measures of percentage wage differences further reduces estimates of the RN wage gap, indicating that RNs are paid wages only moderately above long-run opportunity costs.

Our analysis does not "solve" the RN shortage puzzle stated at the outset, but it does sharply reduce its dimensions. We suggest that increasing demand for RNs combined with barriers to and sluggish growth in RN training can result in periodic shortages and permit RN wages to persist at levels above opportunity costs. Although our analysis focuses on wages rather than total compensation, we provide evidence indicating that results would be largely unaffected if nonwage benefits were included as well. Because evening shift work is common for hospital nurses but is not directly measured in O*NET, we provide a "back of the envelope" estimate of how it would affect the nursing wage gap.

Apart from addressing the wage-employment puzzle among registered nurses, the analysis provides two more general implications. First, labor market wage analyses are enriched through the consideration of job content measures of skill and working conditions. Second, Mincerian log wage differentials are not necessarily appropriate when the tails of the wage distribution differ markedly between treatment and control groups.[3] In what follows we first review theory and evidence on nursing wages and employment. We then discuss construction of the matched CPS/O*NET database and provide evidence on how RNs compare to other college-educated workers in terms of wages, required job skills, and working conditions.

2. Theory and Evidence on Nursing Labor Markets

Competitive labor markets have multiple employers, minimal entry barriers among workers and firms, worker mobility across employers, and good information among workers and employers regarding employment and wage opportunities. Such markets should produce wages that are roughly the same among similarly skilled workers with similar preferences who perform similar levels of work (i.e., skills and working conditions), the so-called "law of one wage."

[3] The first point is a theme addressed in other recent articles, most notably that of Autor and Handel (2009). The second point has been made by Blackburn (2007).

Of course, there is not literally a common wage for identical workers in identical jobs. Even in highly competitive markets, search frictions and idiosyncratic factors (often not measurable) among workers, jobs, and locations generate wage differences. Factors shifting labor demand and supply change continually, so wages move toward but do not mechanically achieve levels that equilibrate demand and supply. Yet if wages are approximately competitive, we do not expect to see a sustained shortage (unfilled vacancies) or sustained surplus of qualified but unemployed applicants.[4]

Because high vacancy levels in nursing positions are common, a natural explanation to consider is monopsonistic power among employers, particularly in hospitals, where a majority of RNs are employed. The canonical competitive model views employers such as hospitals as "price (wage) takers" that face perfectly elastic firm-level nursing supply curves. The pure monopsony model assumes a labor market with a single employer with no mobility across occupations or labor markets. A profit-maximizing monopsonist pays wages below competitive levels and, thus, must reduce employment (output) given a shortage of workers at that wage. Real-world nursing markets do not satisfy the assumptions of pure competition or monopsony. Even in small markets with few nursing employers, RNs have some ability to move between employers and across labor markets. Even in large markets with hundreds of hospital and non-hospital nursing employers, employers do not literally face a horizontal labor supply curve. "New monopsony" models focus on worker-specific attachment to firms and immobility arising from sources other than employer concentration (Bhaskar, Manning, and To 2002; Manning 2003) and expect wages to vary with the elasticity of labor supply.

While monopsony power of hospitals is a potential explanation for shortages, we do not directly address it here. First, there is rather limited direct evidence supporting either classic or new monopsony in nursing markets, with RNs exhibiting substantial mobility across employers.[5] Second, wage studies indicate that RNs earn not less but rather considerably more than similar non-RN employees (Hirsch and Schumacher 2005). If RNs realize sizable wage premiums, shortages are all the more puzzling.

Our focus on the role of job attributes on nursing wages is not without precedent. Although we are unaware of studies emphasizing unmeasured nursing skills, several studies have noted the importance of working conditions with regard to RN labor supply or wages. Shields (2004) suggests that nursing labor supply may be more sensitive to non-pecuniary job aspects than wages, an emphasis seen often among articles in health practitioner journals. Di Tommaso et al. (2009) conclude that nursing labor supply in Norway is relatively inelastic with respect to wages but sensitive to the type of workplace and shift work. A similar finding for Finland is provided by Kankaanranta and Rissanen (2009). There is little literature relating RN wages to workplace disamenities, although Schumacher and Hirsch (1997) examine how RN

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[4] Factors that break down equivalency between spot wages and productivity include firm-specific (i.e., nontransferable) skills, compensation tied to company seniority independent of skill, defined benefit pensions penalizing quits among young workers, earnings linked to group rather than individual productivity, and pay based on time input rather than hard-to-measure output. Nominal wages differ across geographic labor markets as a result of differences in area amenities, prices, productivity (due, say, to agglomeration economies), and state and local fiscal policies (Moretti 2010).

[5] For evidence and references, see Hirsch and Schumacher (2005) and a recent study by Matsudaira (2010). An exception to the generalization in the text is a study by Staiger, Spetz, and Phibbs (2010), who find a very low labor supply elasticity among RNs in Veterans Affairs hospitals.

wages differ based on workplace type and time of shift. Given the potential importance of non-pecuniary job attributes, we explore the role of occupational skills, job tasks, and working conditions on nursing wages as well as the implication of our results in terms of understanding RN shortages.

3. Wage Data from the CPS

Data on individual workers used in our wage analysis are from the CPS Outgoing Rotation Group (ORG) monthly earnings files for January 2005 through June 2008.[6] The CPS-ORG files include the quarter sample of households for whom the earnings supplement is administered. Our sample includes all employed non-student, full-time wage and salary workers who are age 20 and over, who report their earnings (i.e., those with imputed earnings are excluded), and who have an associate degree (academic or vocational), a BA, or an MA.[7]

Our wage is a measure of usual average earnings per hour on one's primary job. The straight-time wage is reported directly in the CPS for hourly workers, including most RNs. This is used as our wage measure for workers without tips, overtime, or commissions. For salaried workers, plus hourly workers receiving supplemental pay, the wage is calculated as usual weekly earnings (inclusive of tips, overtime, and commissions) divided by usual hours worked per week.[8] For the few workers reporting variable usual hours, we use hours worked the previous week to calculate hourly earnings. For workers whose weekly earnings are top-coded (at $2885), mean earnings above the cap are assigned based on gender-specific estimates assuming a Pareto distribution in the upper tail.[9] All earnings figures are stated in January 2008 U.S. dollars. To reduce noise due to recording or reporting errors, a small number of observations with extreme implicit wage values (less than $3 and $150 or greater) are excluded.[10]

As seen in Table 1, average hourly earnings for RNs from 2005 through June 2008 is $29.45, 7.4% more than the $27.43 average for the college control group (means are calculated using sample weights). Focusing instead on the difference in the mean log wage, the RN wage advantage is .178 log points (19.5%), more than double the gap based on arithmetic means.[11]

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[6] As discussed below, the CPS is matched to O*NET data issued in June 2007 based on job analyst and incumbent reports in the months and years preceding the release date.

[7] Part-time workers (defined as less than 35 usual hours worked per week on their principal job) are excluded from the comparison group sample but not the RN sample. Wage differences between full-time and part-time RNs are very small, so results with part-time RNs excluded are nearly identical to those presented.

[8] CPS wage measures include pay resulting from shift work, a topic discussed subsequently.

[9] Estimated mean earnings are about 1.6 times the cap for women and 1.8 times the cap for men. Estimates by gender and year (since 1973) are calculated by Barry Hirsch and David Macpherson and are posted at http://www.unionstats.com.

[10] Bollinger and Chandra (2005) show that trimming (deleting) or winsorizing (recoding) extreme values can induce or exacerbate bias and is generally not justified. They find 1% trimming has little effect, but a level of 5% induces nontrivial bias. We exclude just 0.2% and 0.3% of the RN and control group observations, respectively. Inclusion of the outliers increases mean wages by 9, 14, and 20 cents for RNs, female controls, and male controls, respectively, while at the same time noticeably increasing variance.

[11] Percentage approximations are calculated using $100[\exp(\beta) - 1]$, where β is the coefficient on the RN dummy. As noted by Kennedy (1981), a more precise (but still biased) estimate would account for the variance of the estimate. The Kennedy adjustment reduces most percentage gaps shown in the article by a tenth of 1%.

Table 1. Wages among RNs and the Comparison Group, with and without Imputed Earners

	RNs	College Control Group	Women	Men
Estimation sample: excludes imputed earners				
Real wage	29.45 (11.62)	27.43 (19.40)	23.18 (14.11)	31.11 (22.38)
Log wage	3.3144 (.3716)	3.1398 (.5631)	3.0081 (.5054)	3.2539 (.5852)
Sample size	8292	135,593	64,565	71,028
Full sample: includes imputed earners				
Real wage	28.21 (12.96)	27.37 (19.58)	23.17 (14.45)	30.98 (22.49)
Log wage	3.2456 (.4413)	3.1323 (.5727)	3.0018 (.5168)	3.2447 (.5944)
Sample size	11,514	190,119	90,082	100,037
Nonresponse rate (%)	28.0	28.7	28.3	29.0

Shown are weighted means using CPS sample weights, with standard deviations in parentheses. Samples include those with at least an associate degree and no greater than a MA degree. Samples excluding imputed earners are used in all empirical work. Weighted median wages and median log wages are $27.68 and 3.3207 for RNs and $22.58 and 3.1170 for the college control group. Not shown in the table are means for the imputed sample. The mean imputed dollar wage (log wage) for nonrespondent RNs is $25.30 (3.0849).

The difference reflects a compressed RN (occupation-specific) wage distribution, as compared to the control group's longer right and left tails. The coefficient of variation (CV) of RN wages is 39.5 ([11.62/29.45]100) compared to 70.7 for the comparison group wage.[12] These highly different distributions indicate that something other than the standard approach for estimating percentage wage gaps should be considered (Blackburn 2007).

Excluded from the analysis are workers who do not report their earnings and thus have their hourly wage and/or usual weekly earnings imputed: 28.0% of the RNs and 28.7% of the control group sample. Such exclusion is important since nonresponding nurses (and other workers) are generally assigned earnings of "donors" in other occupations (broad, not detailed, occupation is a donor match criterion). Inclusion of imputed workers causes a substantial attenuation in wage gap estimates (Hirsch and Schumacher 2004; Bollinger and Hirsch 2006). The final sample size following the above exclusions is 143,885, which includes 8292 RNs and 135,593 employees in the college comparison group.

Means for the full sample, including imputed earners, are shown in the bottom portion of Table 1. The impact of imputed values is readily evident. As expected, mean wages for the broad control group are similar for the two samples ($27.43 excluding and $27.37 including imputations). But inclusion of imputed earners, most of whom are likely to be assigned the earnings of a non-RN donor, reduces mean earnings for RNs from $29.45 absent imputations to $28.21 with imputations (mean log wages decline by .069 log points). RNs who report their wage display a 16.4% wage advantage (and a .230 log wage advantage) over the $25.30 (or a 3.085 log point) mean of the imputed wage among nonrespondent RNs.

The importance of gender, absent other covariates, can be seen by breaking out the average male and female wages of the control group. The average RN wage of $29.45 is well above the $23.18 mean wage for college women but below the $31.11 average for college men. Using log points, the RN unadjusted wage advantage is .306 relative to women and .060

[12] Although most occupations have low within-occupation wage dispersion compared to a broad control group, we find that among major occupations RNs exhibit one of the lowest (unconditional) dispersion levels.

relative to men. In the wage analysis that follows, gender is found to be relatively unimportant following conditioning on job attributes.

4. Earnings and Job Tasks: Skill and Working Conditions Indices from O*NET

The O*NET, produced by the U.S. Department of Labor's Employment and Training Administration, is a comprehensive database system for collecting, organizing, and describing data on job characteristics and worker attributes within occupations. Since the release of O*NET 1.0 in 1998, the database has been extended and updated based on input from job analysts and job incumbents. O*NET replaces the Dictionary of Occupational Titles (DOT), used in numerous studies by economists and other social scientists (recent examples include Autor, Levy, and Murnane 2003; Ingram and Neumann 2006). Use of O*NET in economic studies is limited but rapidly growing.[13]

We use O*NET 12.0, released in June 2007, and we created a data set with 259 O*NET occupational job descriptors (from an initial 488 descriptors in the database).[14] The job descriptors cover a wide range of attributes, including abilities that influence the acquisition and application of knowledge in problem solving to psychomotor, physical, and sensory abilities to social, technical, and complex problem-solving skills. Most O*NET variables involve required workplace tasks or skills necessary to successfully perform a job or conditions faced by workers in a given occupation. We construct multiple indices of skill-related job tasks and physical working conditions from the O*NET database using factor analysis.

To examine how pay varies with job attributes, the O*NET measures are merged with CPS data on individual workers. O*NET and the CPS identify detailed occupations using Standard Occupational Classification (SOC) codes. The CPS identifies workers in 502 civilian SOC categories, whereas O*NET provides a more detailed SOC breakdown, with 798 civilian occupations. The crosswalk between O*NET and the CPS occupations is reasonably straightforward.[15]

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[13] Hirsch (2005) matches O*NET job attributes to the CPS to help explain wage differences between part- and full-time workers. Autor and Handel (2009) compare O*NET occupation measures with worker-reported job task measures included in a special survey. Abraham and Spletzer (2009) match O*NET measures to the CPS and the Occupational Employment Statistics (OES) in order to analyze the returns to job skills. Perri and Sparber (2009) use O*NET measures of physical tasks and language ability requirements among the jobs held by immigrant and native workers to analyze how immigration affects job task specialization and relative wages. Chiswick and Miller (2010) use O*NET language requirement measures and the 2000 U.S. Census to better understand earnings and the matching of immigrants to jobs.

[14] The CPS/O*NET database was created jointly by one of the authors and economists at Global Insight. Most O*NET job descriptors are measured using an "importance" and a "level" scale, with these values being highly correlated. Descriptors measured in level form were retained and the "duplicative" descriptors eliminated, reducing the number of O*NET descriptors from 488 to 259 with little loss in information. A small number of mainly small occupations had not yet released revised ratings since the initial version of O*NET.

[15] There is a one-to-one match from O*NET to the CPS for 316 occupations, including RNs. Most of the remaining involve a mapping of two or more O*NET occupations to a CPS category. In these cases, O*NET descriptor values are calculated based on the weighted average across the component O*NET occupations, using May 2005 employment reported in the OES as weights. A small number of CPS occupational categories are made up of a combination of O*NET categories defined at such a fine level of detail that OES employment figures are not available. In these cases, component O*NET occupations are assigned equal weights. A small number of CPS occupations are identified as "all other" categories (e.g., "information and records clerks, other"), for which there are no O*NET ratings. These CPS occupation codes were assigned O*NET values based on average ratings (using employment weights) among similar occupations.

The merged CPS/O*NET database allows us to address whether a CPS-only analysis understates or overstates the nursing wage gap. CPS variables account for individual worker characteristics but not job attributes. Combining O*NET with the CPS allows us to account more directly for occupational skill requirements, job tasks, and working conditions that influence wages.[16] Because worker skills are measured imperfectly by schooling, potential experience, and other variables in the CPS, accounting for job tasks also helps control for worker-specific skills.

There is no consensus regarding a best method for collapsing a large number of occupational job descriptors into a few informative variables. We opt for a relatively simple approach, using factor analysis to create a single index measure of working conditions and four "skill/job task" indices. We use 206 of the total 259 O*NET variables in our database.[17] Of these 206 attributes, 38 physical working conditions measures are used to create a single index of working conditions. The remaining 168 job descriptors are used to construct indices of job skill/tasks based on the first four factors. Factors beyond the first four had relatively low eigenvalues and provide minimal additional information.[18]

The factor analysis constructs multiple occupational indices that reflect a "principled" collapsing of O*NET skill/task and working condition attributes.[19] The factor indices are constructed independently of the CPS wage data that they are intended to help explain. The first factor loads all O*NET attributes in a way that accounts for a maximum proportion of the covariance across attributes and occupations. A second factor accounts for a maximum proportion of the remaining covariance, and so forth. Our factor analysis is weighted by occupational employment, compiled from the CPS for all wage and salary workers. By construction, the factors have a mean of 0 and standard deviation of 1.0 across the entire workforce. These factors and their loadings are described below.

Based on its factor loadings, we title skill/task factor 1 (*SK1*) "cognitive skills." *SK1* accounts for 41% of the total covariance among the 168 skill/task attributes across the 501 Census occupations. *SK1* heavily loads such O*NET measures as critical thinking, judgment and decision making, monitoring, written expression, speaking, writing, active listening, written comprehension, active learning, negotiation, and persuasion. Skill/task factor 2 (*SK2*), titled "mechanical skills," accounts for 14% of the covariance and heavily loads measures such as mechanical skills, repairing and maintaining equipment, installation, troubleshooting, and operation monitoring and control. Skill/task factor 3 (*SK3*), which we title "assisting and caring for others," accounts for 7% of the covariance and heavily loads measures such as assisting and caring for others, responsibility for others' health and safety, concern for others, and

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[16] Autor and Handel (2009) and Ingram and Neumann (2006) discuss the advantages of using job (occupation) attributes in addition to or instead of individual attributes in order to measure the returns to skill. Ingram and Neumann provide a careful discussion of factor analysis, which they use to create skill indices from the DOT.

[17] Excluded were 26 "physical ability" attributes (e.g., finger dexterity, gross body coordination, and near vision) that can be considered neither workplace disamenities nor scarce compensable skills; six worker "Interest" attributes (investigative, social, realistic, etc.); and a set of 21 "Values" attributes (how well does this occupation satisfy needs for ability utilization, compensation, helping others, etc.) intended to help train and match individuals with appropriate occupations.

[18] The analysis attempts to control for relevant (i.e., wage-determining) job attributes based on multiple measures, each of which is an imperfect proxy for the underlying wage determinant. Lubotsky and Wittenberg (2005) show that in such situations, the use of multiple proxies rather than a single measure reduces bias on the variable of interest. Bollinger and Minier (2009) extend their analysis and show that use of a single proxy (or too few proxies) may also bias coefficients on other correctly measured variables.

[19] Descriptions of factor analysis are provided in Gorsuch (1983) and Ingram and Neumann (2006).

knowledge in various medical, science, and social science fields relevant to occupations involving assistance to others. Skill/task factor 4 (*SK4*), which we title "administration, management, and sales," accounts for 5% of the covariance and heavily loads skill/task variables reflecting sales and marketing knowledge; responsibility for outcomes and results; staffing organizational units; selling or influencing others; monitoring and controlling resources; guiding, directing, and motivating subordinates; management of personnel resources; and dealing with external customers.

Factor index *WC* accounts for 56% of the total covariance among the 38 working condition attributes. *WC* includes job attributes typically included in studies of compensating differentials. *WC* heavily loads attributes such as dynamic and static strength; very hot and cold temperatures; extremely bright or inadequate lighting; exposure to contaminants; cramped work space or awkward position; exposure to burns, cuts, bites, or stings; and exposure to hazardous equipment. As is widely recognized, it is difficult to identify compensable working conditions, in part because heterogeneous worker preferences influence occupational choice (worker-job sorting), and because workers with high wages (for reasons that cannot be fully controlled) tend to sort into jobs with fewer disamenities (Hwang, Reed, and Hubbard 1992).

Using the merged CPS/O*NET database, we provide descriptive evidence comparing skill/task and working condition attributes for RNs and college-educated workers economy-wide. Note that the O*NET evaluation of the RN occupation represents an average across multiple RN jobs in and outside of hospitals. The CPS also provides a single RN occupation code but allows one to identify the industry of employment (e.g., hospitals). Because the composite O*NET ratings apply to an average across all RNs, our analysis does not make a distinction among RNs employed in different settings. Table 2 provides the means of the O*NET indices for RNs and the comparison group, shown jointly and separately by gender. Index *SK1* (cognitive skills/tasks), the first principal factor constructed from the 168 O*NET job descriptors, is an extremely strong correlate of earnings. The college workforce (i.e., those with associate, BA, and MA degrees, excluding RNs) has a mean *SK1* of .63, with equivalent values for women and men, substantially higher than the zero mean for all wage and salary workers. The standard deviation is .81, slightly below the 1.0 value for the economy-wide sample. RNs exhibit a substantially higher *SK1* index rating in O*NET than does the college control group, a 1.10 value that is more than a half standard deviation higher than the control group mean of .63.

The additional skill/task-related factors account for far less of the total variation in job attributes and are more weakly related to earnings than is *SK1*. As expected, mean *SK2* (mechanical skills/tasks) among college-educated women is far below the average across the male average (−0.46 vs. 0.33). The RN value of −0.44 is nearly identical to the female average. The third index, *SK3* (assisting and caring), heavily weights job requirements related to assisting the health and well-being of others. The mean for college women is .01, effectively equal to the economy-wide average; college men have a substantially lower average of −0.32. Not surprisingly, RNs have one of the highest averages across all occupations, with a *SK3* factor index value of 2.08, two standard deviations above the economy-wide average.[20]

Turning to working conditions, the college workforce has a mean *WC* value of −.48, −.65 among women and −.27 among men. The negative value for *WC* and positive value for *SK1* reflect the relatively good working conditions and high level of skills that typically characterize

[20] Folbre and Nelson (2000) argue that jobs involving caring are more likely to attract women and pay less. We find that *SK3* (assisting and caring tasks) enters negatively and significantly into wage equations.

Table 2. O*NET Skill and Working Condition Indices: Means by Group

	RNs	College Control Group	Women	Men	Simple Wage Correlation	
					Women	Men
SK1—Cognitive skills	1.10	0.63 (0.81)	0.63 (0.77)	0.63 (0.84)	0.41	0.41
SK2—Mechanical skills	−0.44	−0.04 (1.00)	−0.46 (0.78)	0.33 (1.03)	0.20	0.08
SK3—Assisting and caring	2.08	−0.17 (1.17)	0.01 (1.26)	−0.32 (1.06)	−0.08	−0.25
SK4—Administration, management, and sales	−1.52	−0.08 (1.12)	−0.21 (1.02)	0.03 (1.19)	0.09	0.03
WC	0.29	−0.48 (0.81)	−0.65 (.53)	−0.27 (0.96)	−0.15	−0.26
Sample size	8292	135,593	64,565	71,028		

Shown are weighted means, with standard deviations in parentheses. Weighted correlations between the O*NET factor indices and wages are for the female and male college comparison groups. All RNs are assigned uniform O*NET attribute values.

Table 3a. O*NET Skill Attributes for Which RNs Rate High: Percentile Rank and Wage Correlations

Description	RN Rank	Simple Wage Correlation
Abilities—enduring attributes of the individual that influence performance		
Problem sensitivity	96	0.32
Inductive reasoning	93	0.37
Oral comprehension	85	0.38
Deductive reasoning	78	0.42
Skills—developed capacities that facilitate learning, the more rapid acquisition of knowledge, or performance of activities that occur across jobs		
Service orientation	92	0.21
Social perceptiveness	90	0.17
Science	88	0.27
Critical thinking	87	0.37
Work activities—types of job behaviors occurring on multiple jobs		
Assisting and caring for others	96	−0.01
Identifying objects, actions, and events	95	0.26
Documenting/recording information	95	0.23
Monitor processes, materials, or surroundings	91	0.20
Work context—physical and social factors that influence the nature of work		
Consequence of error	96	0.27
Work with work group or team	91	0.17
Responsible for others' health and safety	89	0.03
Frequency of decision making	89	0.18
Work style—personal characteristics that can affect how well someone performs a job		
Concern for others	95	−0.08
Self control	95	−0.06
Adaptability/flexibility	95	0.12
Cooperation	94	−0.03

jobs among college-educated workers. The RN occupation receives a *WC* factor score of .29, nearly a full standard deviation above the college workforce mean. In short, O*NET evaluates RN jobs as requiring substantially higher cognitive skills and more demanding working conditions than a typical job for college-educated workers. Other broad measures of required occupational skills/tasks (*SK2–SK4*) among college workers are similar to or slightly below the averages across all wage and salary workers.

Space does not permit presenting values for all O*NET job attributes, but examples of skill attributes in which RNs are ranked high or low are provided in Tables 3a and 3b, along with the simple correlation of each attribute with wages. By ordering workers in the college sample based on the values on each O*NET attribute, percentile rankings for RNs can be compiled. RNs rank near the 90th percentile or higher for several measures. RNs rate high on required abilities in problem sensitivity and inductive reasoning; on the skills of service orientation and social

Table 3b. O*NET Skill Attributes for Which RNs Rate Low: Percentile Rank and Wage Correlations

Description	RN Rank	Simple Wage Correlation
Abilities—enduring attributes of the individual that influence performance		
Mathematical reasoning	6	0.27
Visualization	7	0.12
Number facility	8	0.19
Skills—developed capacities that facilitate learning, the more rapid acquisition of knowledge, or performance of activities that occur across jobs		
Management of financial resources	10	0.25
Installation	16	0.19
Programming	17	0.25
Work activities—types of job behaviors occurring on multiple jobs		
Scheduling work and activities	19	0.23
Communicating with persons outside organization	21	0.26
Interacting with computers	23	0.27
Work context—physical and social factors that influence the nature of work		
Degree of automation	18	0.07
Electronic mail	26	0.31
Level of competition	29	0.24
Work style—personal characteristics that can affect how well someone performs a job[a]		
Persistence	61	0.22
Leadership	62	0.17
Innovation	68	0.20

[a] RNs were in the 61st or higher percentile for all attributes in this group.

perspectives; on the work activities of identifying objects, actions, and events, and documenting/recording information; and on work context attributes measuring the consequence of error and frequency of decision making. Many of these job attributes display a strong correlation with wages. RNs also rank high in some attributes weakly or negatively correlated with wages, for example, concern for others, assisting and caring for others, working with a work group or team, and adaptability/flexibility. Evident in Table 3b is that RNs rank low in some attributes that are strong wage correlates. These include mathematical reasoning, management of financial resources, programming skills, scheduling work and activities, communicating with persons outside one's organization, interacting with computers, the level of competition, and use of E-mail.

Table 4 provides a comparison between RNs and the college control group for 19 of the 38 O*NET working condition attributes included in our *WC* index.[21] The high percentile rankings

[21] Omitted from the table are two "indoors" variables that are largely collinear with the outdoors variables; nine variables that measure "time spent" in physical activities, such as sitting, standing, using hands, etc.; five strength variables; and three work context variables measuring conflict situations and dealing with unpleasant or physically aggressive people.

Table 4. Selected Working Condition Index (WC) Components and the Percentile Rank of RNs

Description	RN Rank
Physical working conditions attributes included in *WC*	
Physical proximity to others	95
Exposed to radiation	95
Exposed to disease or infections	95
Wear specialized protective or safety equipment	93
Cramped work space, awkward positions	93
Wear common protective or safety equipment	91
Exposed to hazardous conditions	88
Exposed to contaminants	88
Sounds, noise distracting or uncomfortable	83
Exposed to minor burns, cuts, bites, or stings	83
Extremely bright or inadequate lighting	81
Exposed to whole body vibration	70
Exposed to hazardous equipment	60
Outdoors, under cover	47
In an enclosed vehicle or equipment	37
Very hot or cold temperatures	32
Exposed to high places	32
Outdoors, exposed to weather	23
In an open vehicle or equipment	11

Working condition index *WC* is described in the text.

among RNs reflect not only their demanding working conditions but also the relatively low number of physical workplace disamenities in jobs populated by college-educated workers. Among the working conditions in which RNs rank high are exposure to radiation, disease, infection, hazardous conditions, and contaminants; physical proximity to others; cramped work space or positions; and the wearing of protective or safety equipment. RNs rank low in exposure to the elements, working in vehicles or equipment, exposure to extreme temperatures, and exposure to high places.

The descriptive data from O*NET are revealing. They show that for a large number of workplace skills and abilities, nursing jobs are evaluated as requiring a high level of skill. At the same time, nursing involves several demanding working conditions.[22] Thus, some portion of the "high" RN wage is likely to result from skills and working conditions not reflected in typical wage analyses. We now turn to wages, first using standard analysis and then introducing the O*NET job attributes.

5. Wage Analysis Using CPS Worker, Location, and Job Attributes

In this section, we provide "CPS-only" regression analysis comparing wages among RNs and our comparison group of college-trained workers, with controls for individual and location characteristics. By these measures, RNs are paid very well. We then extend the analysis to include the O*NET indices accounting for job attributes.

[22] In work not shown, we compile descriptive evidence on O*NET "work value" descriptors not included in the wage analysis. The nursing occupation tends to satisfy the specific needs associated with workers who value social service, activity, co-workers, achievement, ability utilization, social status, and security. It is ranked low with respect to satisfying needs for recognition, independence, working conditions, and company policies and practices.

Wage regression estimates of the RN gap are presented in Table 5, using both a mixed female/male comparison group with a gender dummy included and, for comparison, a female-only comparison group.[23] The CPS-only log wage equations include potential experience (i.e., years since schooling completed) in quartic form, plus dummy variables for gender, BA and MA degrees (vs. associate degree), race/ethnicity (three dummies for four groups), marital status (2), foreign-born (citizen and noncitizen), year (3), city size (6), and region (8). The unadjusted RN wage advantage is .182 log points relative to all college-educated workers, as compared to .311 log points if the comparison group is restricted to women.

Standard log wage regression analysis, shown in line 1, indicates that RNs receive a large wage premium of .325 log points (38.4%) compared to other college-educated workers. Using an all-female control group, the RN wage advantage increases .03 log points, from .325 to .355. Using the combined sample, moving from the unadjusted to the regression wage differential substantially increases the RN gap (from .182 to .325), primarily as a result of the inclusion of the gender dummy, effectively creating a female comparison group for 93% of the RN sample. Using the all-female comparison group, the unadjusted and regression wage gaps are roughly similar (.311 and .355), indicating that the comparison group choice based on education is a reasonable one.[24]

We next use the merged CPS/O*NET database to incorporate job attributes and worker characteristics into the wage analysis. Our approach is straightforward. We compare RN wage gaps from standard log wage regressions with and without control for the O*NET factor indices measuring workplace skills/tasks and working conditions, shown previously in Table 2 (*SK1–SK4* and *WC*).[25] In preliminary analysis, we find that the relationship between log wages and several of the job indices is highly nonlinear. Hence, we utilize a specification that includes each of the indices in cubic form.[26]

Row 1 of Table 5 shows RN log wage gap estimates based on use of OLS and the standard Mincer form, with the percentage estimates based on exponentiated logs. Adding the O*NET job attribute indices to the log wage equation reduces the RN gap estimate by .12 log points, from .325, as seen previously, to .201, or from 38% to 22%. This large reduction in the wage gap reflects the strong impact of both first factor *SK1*, which heavily loads on cognitive skill measures and is strongly correlated with wages, and the working conditions index, *WC*. For both *SK1* and *WC*, the RN occupation is rated highly as compared to the non-RN comparison group (as seen in Table 2). The *WC* results are interesting. At the mean of the sample, *WC* (in cubic form) has a modest negative relationship with wages, while at higher levels of the index, such as those seen for RNs, there is strong evidence of compensating wage differentials.[27]

[23] Whereas prior tables have presented descriptive evidence using sample weights, regression estimates are unweighted. Weighted least squares results using CPS sample weights produce similar estimates.

[24] In order to isolate the effect of changing the comparison group, we retain male nurses and keep the same RN sample. Since wage differences between male and female nurses are small, results are little affected.

[25] Because multiple workers are assigned common O*NET values for each occupation, all regression standard errors are clustered on occupation. Absent clustering, standard errors are roughly a tenth as large as those shown.

[26] RN wage gap estimates show some sensitivity in moving from single to higher-order terms of the indices since RNs have relatively high and low values for several of the indices. Gap estimates change little, however, when terms beyond the cubic are added. Because O*NET job attributes are measured at the occupation rather than the worker level, measurement error may cause attenuation of coefficient estimates. Because of space constraints, we do not present coefficients on the O*NET indices, focusing instead on RN wage gap estimates.

[27] Although measuring compensating differentials is notoriously difficult owing to negative correlation between workplace disamenities and unmeasured skills, the O*NET skill indices control for many of these skills.

Table 5. RN/College Regression Wage Gaps, Alternative Specifications and Estimation Approaches

	Mixed Comparison Group, Gender Dummy			Female Comparison Group		
	Raw Gap	CPS Controls	Plus O*NET	Raw Gap	CPS Only	Plus O*NET
1. Mincer OLS log and percentage wage gaps						
Log gap	0.182	0.325	0.201	0.311	0.355	0.160
SE	0.030	0.021	0.046	0.025	0.022	0.057
As %	20.0	38.4	22.2	36.5	42.6	17.3
2. Dollar and percentage wage gaps from OLS linear wage model with interactions						
Dollar gap	$2.21	$6.54	$4.25	$6.28	$7.27	$3.33
SE	$1.01	$0.55	$1.35	$0.63	$0.54	$1.48
As %	8.2	29.0	17.1	27.5	33.3	12.9
3. Negative binomial log gaps						
Log gap	0.079	0.284	0.194	0.243	0.312	0.130
SE	0.038	0.023	0.050	0.027	0.024	0.061
As %	8.2	32.8	21.5	27.5	36.6	13.9
No. RNs		8292			8292	
No. controls		135,593			64,565	
No. total sample		143,885			72,857	

Estimates are from unweighted regressions. Shown on the left side are RN wage gaps with a pooled female and male college-educated comparison group. On the right side are results with an all-female control group. Log and dollar gaps are the coefficients (standard error, SE) on an RN dummy variable. CPS controls include potential experience (i.e., years since schooling completed) in quartic form, plus dummy variables for gender (left-side results only), BA and MA degrees (vs. associate degree), race/ethnicity (three dummies for four groups), marital status (2), foreign-born (citizen and noncitizen), year (3), city size (6), and region (8). O*NET variables measuring skill and working conditions are factor indices *SK1* through *SK4* and *WC*, each in cubic form. Log gaps (β) shown above are converted to percentages by 100[exp(β) − 1]. Percentage dollar gaps are calculated by $\left[\left(\overline{W}_{RN}-\overline{W}_{C}\right)/\overline{W}_{C}\right]100$, where the numerator is the estimated dollar gap and $\overline{W}_{C}$ is calculated by $\overline{W}_{RN}$ minus the gap, with $\overline{W}_{RN}$ equal to $29.08 (in January 2008 U.S. dollars). Standard errors are clustered on occupation.

Using the female-only comparison group, once we account for job skills/tasks and working conditions, the estimated RN differential is lower with the all-female control group than with the mixed-gender group conditioning on gender, .16 versus .20 (17% vs. 22%). This difference is driven by relatively large estimated effects of adverse working conditions in the female-only sample, a result noted previously in the literature (Hersch 1998), coupled with more adverse working conditions among RNs than among other college-educated women. The impact of the O*NET skill indices differs little between men and women. In short, the treatment of gender in the wage analysis matters far less once one conditions on occupational job skill/task requirements and working conditions.[28]

Our analysis to this point shows that nursing is evaluated as requiring a high degree of skills, that job skill/task requirements are strongly related to wages across the labor market, and that RN log wage gap estimates decline sharply following control for these job attributes. These estimates, however, continue to indicate a sizable RN wage advantage relative to long-run

[28] In fact, results are highly similar using the mixed gender comparison group without the gender dummy.

opportunity costs, a result seemingly at odds with evidence of systematic nursing shortages. We further explore this puzzle below.

6. Do Estimates from the Mincer Equation Overstate Relative Nursing Wages?

Descriptive evidence on weighted mean wages, seen in Table 1, revealed large differences between RN wage gaps based on percentage differences in mean dollars and differences in mean logs converted to a percentage. The same is true for means based on unweighted data used in the statistical analysis. As seen in Table 5, the raw log wage difference between RNs and the comparison group is .182 log points, or about 20.0%. In contrast, the percentage difference in mean dollar wages, $(\overline{W}_{RN} - \overline{W}_C)/\overline{W}_C$, is only 8.2%. The highly compressed distribution of RN wages, as compared to the comparison group (i.e., thinner left and right tails), causes the log wage gap (exponentiated) to provide a poor approximation of the percentage difference in arithmetic means, at least for wage gaps absent controls.

Although the Mincerian semi-log wage equation remains the standard approach for estimating percentage wage gaps in labor economics, Blackburn (2007) shows that it is not appropriate in some applications and recommends an alternative nonparametric approach for estimation of the Mincer equation.[29] The Mincer model holds that

$$W = e^{x\beta}u.$$

If u is homoskedastic then the model can be written and estimated in its standard semi-log form, thus:

$$\ln W = x\beta + u.$$

The semi-log model provides consistent estimates of β only under the assumption that the distribution of the error term is independent of the regressors. In our case the assumption of homoskedasticity is (grossly) violated since the error distribution is correlated with the RN indicator variable.

Below we provide estimates of the RN percentage wage gap using alternative methods. First, we calculate the percentage differential from wage equations with the dollar wage rather than log wage as the dependent variable, while interacting right-hand-side variables with all the experience and schooling terms to allow nonlinear (i.e., multiplicative rather than additive) wage effects, as predicted by human capital theory and modeled in the Mincer equation. Second, we estimate the wage equation using a negative binomial general linear model (GLM) with a log link, which allows for an alternative (more flexible) error distribution than does OLS while retaining the assumption that the Mincer model is the correct specification.[30] Third, we provide a check on results by estimating RN percentage gaps from propensity score-matching models that do not rely on the functional form of the wage equation. The matching approach, used widely in recent years (e.g., see references in Imbens [2004]), allows direct calculation of both the exponentiated log and arithmetic percentage wage gaps based on the same sample of

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[29] For a distinct but related discussion on the use and interpretation of log models, see Manning (1998).

[30] We thank Amitabh Chandra for suggesting this approach. It is similar to the estimation strategy taken by Blackburn (2007), although not his preferred method.

RNs and a matched control group of non-RNs based on their similarity to the RN "treatment" group (i.e., similar propensity scores that reflect the probability of being an RN).[31]

Table 5 provides alternative estimates of the RN percentage wage gaps using these alternative approaches. The unadjusted log gap is .182 based on the mixed-gender comparison group and .311 using the female-only comparison group, while the benchmark CPS-only log (percentage) gap estimates are .325 (38.4%) and .355 (42.6%) using the mixed-gender and female-only comparison groups, respectively. Corresponding estimates, controlling for O*NET job attributes, are .201 (22.2%) and .160 (17.3%).

Our alternative approaches clearly show that percentage estimates from an exponentiated OLS log gap overstate the RN wage differential. In line 2 of Table 5, direct calculation of the arithmetic percentage RN gap from a linear wage regression model (with interaction terms) produces gap estimates that are roughly 10 percentage points lower than those seen previously using the standard CPS-only model, from 38.4% to 29.0% for the mixed control group and from 42.6% to 33.3% with the female control group. The same qualitative results occur with the augmented O*NET job attribute estimates, although the differences are about half as large with these densely specified models. Direct calculation of the arithmetic percentages reduces the CPS/O*NET RN gap estimates from 22.2% to 17.1% with the mixed-gender control group and from 17.3% to 12.9% with the female control group.[32] In short, standard OLS estimates of the Mincerian gap substantially overstate relative RN wage differentials.

We obtain similar estimates using the GLM negative binomial log link estimates, as seen in line 3 of Table 5. This approach provides estimates of the Mincer model using less restrictive assumptions regarding the error term distribution. In the CPS-only estimates with the mixed control group, the GLM estimate is .284, or 32.8%, much lower than the standard OLS estimate of 38.4% and modestly higher than the 29.0% obtained from the linear model. Using the female control group, the GLM estimate is 36.6%, in between the standard 42.6% estimate and the 33.3% estimate from the linear model. The GLM estimate for our preferred CPS/O*NET model is .194, or 21.5%, using the mixed-gender sample and .130, or 13.9%, using the female-only control group, in each case being between the standard OLS and linear model estimates. These results indicate that GLM estimation of the Mincer model provides a reasonable alternative to standard OLS estimation. We would argue (as does Blackburn [2007]) that use of such models warrants consideration as a standard robustness check. It is particularly important that such an approach be considered in applications in which conditional or unconditional wage distributions differ greatly between comparison and control groups.

A third approach we consider is the use of propensity score-matching models to estimate RN percentage wage gaps. The matching approach addresses two concerns. First, matching methods explicitly create non-RN control groups of workers based on their similarity to the RN "treatment" group. Thus, matching methods permit us to check if RN regression wage gap estimates are sensitive to the perhaps-inappropriate data support or weighting of non-RNs implicit in OLS. Second, matching estimators allows us to directly compile not only the log

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31 A referee suggested a fourth approach—the use of quantile regression given the compressed distribution of RNs wages relative to the control group. As expected, quantile regressions result in RN wage gap estimates that decrease as one moves from low to high quantiles. This pattern is strong absent controls and using the CPS-only specification, but it is greatly reduced in the specification with O*NET job attribute measures.

32 Percentage dollar gap estimates are calculated by $[(\overline{W}_{RN}-\overline{W}_C)/\overline{W}_C]100$, where $(\overline{W}_{RN}-\overline{W}_C)$ is measured by the regression estimate of the conditional dollar gap and the counterfactual $\overline{W}_C$ is calculated as $\overline{W}_{RN}$ minus the gap. The unweighted mean $\overline{W}_{RN}$ equals $29.08 (in January 2008 U.S. dollars).

Table 6. RN/College Wage Gaps with Nearest Neighbor Propensity Score Matched Samples

	Mixed Comparison Group			Female Comparison Group		
		CPS Controls	Plus O*NET		CPS Controls	Plus O*NET
	ATT	OLS Gap	OLS Gap	ATT	OLS Gap	OLS Gap
1. Log gap	0.333	0.328	0.124	0.351	0.350	0.141
SE	0.008	0.024	0.060	0.008	0.023	0.061
As %	39.5	38.8	13.3	42.1	42.0	15.2
2. Dollar gap	$6.77	$6.71	$2.41	$7.29	$7.31	$3.21
SE	$0.22	$0.62	$1.58	$0.21	$0.58	$1.53
As %	30.3	30.0	9.0	33.4	33.6	12.4
No. RNs		8292			8292	
No. unique matches		6859			6678	
No. total sample		15,151			14,970	

Results are unweighted. Shown on the left side are RN wage gaps with a mixed female and male comparison group identified by nearest neighbor propensity score matching with replacement (excluding ties), with the RN logit model including all CPS controls from the wage equation, including gender (see Table 5 note), plus selected interaction terms. The right-side analysis is identical, except that RNs are matched to an all-female comparison group. The OLS log wage and dollar wage regressions are based on the identical matched samples, with the specifications equivalent to the OLS-only and O*NET-augmented specifications seen in Table 5. OLS standard errors are clustered on occupation, but the matching ATT standard errors are not.

wage gap (i.e., the average treatment effect on the treated, or ATT, in log differences) but also the percentage difference in the dollar ATT between the same RNs and the control group.

The propensity score-matching differentials are estimated as follows. First, a logit model estimates propensity scores that measure the likelihood of workers being an RN, conditional on the explanatory variables previously included in the wage equations.[33] All individuals are ordered from low to high based on their propensity scores. Each "treatment-group" RN is then matched to "control group" non-RNs using nearest neighbor matching, which for each RN searches up and down in the propensity score distribution for the non-RN with the closest score. We match with replacement in order to insure selection of the closest matches and use a single control group match for each "treated" RN (i.e., "ties" are excluded). Matching results are not sensitive to the specific methods and options used. Propensity scores are estimated without inclusion of the O*NET occupational indices, letting the determinants of RN employment be based entirely on pre-market characteristics and not on job attributes. Results from these models are directly comparable to the CPS-only regression results. In practical terms, we are unable to estimate RN logit models with a rich set of O*NET variables because such models perfectly predict RN employment. However, we can estimate CPS/O*NET regression wage equations using the RNs and the matched control group sample obtained from the CPS-only logit model (Imbens and Wooldridge 2009).

Table 6 provides the log and dollar RN wage gaps based on the matching estimators using CPS–propensity score conditioning variables. These estimates are virtually identical to those obtained from the CPS-only regression analysis. For example, using the mixed comparison group, the log wage ATT (i.e., the difference between mean log wages for RNs and their matched comparison group) is .333, or 39.5%, while the ATT using the percentage difference in

[33] The matching models are estimated using Stata procedure psmatch2. Our logit models add interaction terms between several of the explanatory variables (e.g., gender and potential experience, marital status and education, and foreign-born status and education). Estimates are nearly identical using probit rather than logit estimation.

mean dollar wages is 30.3% (column 1 of Table 6). This compares to earlier OLS estimates of 38.4% and 29.0%, respectively. Thus, narrowing the comparison group (the support) to those with similar CPS attributes has little impact on estimates. Similarly, running OLS regressions on the RN/nearest-neighbor matched sample (columns 2 and 3 for the mixed-gender and female-only samples, respectively), either with or without the O*NET variables, produces estimates nearly identical to those seen previously in Table 5.

In summary, standard Mincerian log wage analysis using data on worker and location attributes implies large RN wage premiums of about 40%. These estimates greatly overstate relative RN wages for two reasons. First, they fail to account for the high level of compensable skills/tasks required for RNs and their relatively demanding working conditions. Second, the more compressed distribution of wages among RNs compared to their control group causes standard OLS estimates of the Mincer equation to substantially overstate estimates of RN log and percentage wage gaps. Accounting for occupational job attributes and estimating percentage wage gaps using arguably preferable methods produce RN wage gap estimates of about 15% rather than 40%. Once one accounts for detailed job characteristics, the choice of a female-only or mixed-gender comparison group (with a gender dummy) makes little difference. In short, wages for RNs are far closer to long-run opportunity costs than standard analysis indicates, making regular shortages among RNs less puzzling. That being said, a 15% wage advantage, although far less than 40%, is neither zero nor negative. Absent evidence for nursing wages below opportunity costs, as implied by the monopsony model, nursing shortages remain a puzzle, albeit a less serious one than has been implied by prior wage analyses. We return to this issue in the concluding section.

7. Robustness Checks and Caveats

In addition to the results previously presented, our key results proved invariant to other robustnesss checks. Issues raised by referees included exclusion of those with allocated occupation, estimation of a sample consisting entirely of those with BA degrees, and separate estimates for samples in their first and second years in the CPS. Additional issues are whether gap estimates should be based on the control group wage equation parameters and whether union status should be included as a wage equation control variable.

Omission of the .1% of workers with occupation imputed (following omission of imputed earners) changes log wage gap coefficient estimates at the fourth decimal place. Estimation using only nurse and control group BAs reduced the combined sample by 47%. This had surprisingly little effect on the raw log gap (change at the third decimal point), it moderately lowered the CPS-only RN gap estimates, and it had little effect on the CPS-O*NET estimates.[34] Because households are in CPS outgoing rotation groups 4 and 8 in the same month in consecutive years, a significant portion of the sample is included in the sample during two years. Separate estimates for rotation groups 4 and 8 eliminate all overlap, thus proving that they are unique samples. These two samples produce highly similar estimates, with all differences in log wage gaps at the third decimal place.

The RN log gaps presented in this article are based on intercept shifts for RNs in a pooled wage equation. This approach was chosen in large part for ease of presentation. If the

[34] The rationale for a BA-only analysis is that education investments among RNs and non-RNs with BAs would be more comparable than for RNs with diploma or associate degree certification or with graduate education.

"treatment" group is sufficiently small, slope coefficient estimates in the pooled sample will be close to those from a control group wage equation. Thus, wage gap estimates using the dummy variable approach should closely approximate Blinder-Oaxaca gap estimates using control group slopes to calculate the explained portion of the gap. As the treatment group becomes large, substantive differences in slopes may arise. RNs form a sufficiently large occupation to have some impact on market-wide wage parameters. However, when we recalculate RN gap estimates using control group–only wage equation parameters, all log gap estimates are nearly identical to those obtained from the pooled equations, differences being no larger than .002.

A final issue is treatment of union status, which we did not include in the wage equations. Control variables (e.g., schooling) generally are intended to capture equalizing wage differentials associated with skills, working conditions, and location. Arguably, the union wage advantage largely reflects a premium above opportunity costs and should not be netted out of the RN wage gap. Adding union membership to the wage equation, however, has virtually no effect on estimated RN differentials: The reason is that among college-educated workers, union premiums estimated in a cross section are close to zero.[35] Thus, the decision of whether or not to include union status as a control does not affect the results.

Finally, prior analysis showed that RN wages are far less dispersed than are control group wages; in fact, RN wages are less dispersed than are wages for most occupations (see footnote 12). In a related vein, O*NET evaluates nursing highly as an occupation that satisfies workers who value security (see footnote 22). To the extent that wage and employment risk are not captured in our job attribute indices, this would cause us to understate RN relative wages by some unknown degree.

8. Other Explanations for "High" Wages? Benefits and Shift Work

This study focuses on earnings differences between RNs and similar workers and jobs. A more complete analysis would account for nonwage benefits and focus on total compensation. Unfortunately, household data providing information on worker attributes generally do not report the dollar costs of benefits, while business surveys providing information on benefit costs do not report worker characteristics. Hence, multivariate analysis of RN benefits relative to a control group is not possible.

Published data on employer benefit costs for RNs, however, indicate that benefits for RNs during the period under study are no larger—and indeed are probably smaller—than for workers economy-wide. The Employer Costs for Employee Compensation (ECEC) (U.S. Bureau of Labor Statistics [BLS] 2008a) provides data on compensation, dividing it between wages and salaries versus benefits, the latter including a comprehensive set of voluntary and mandated benefits (mandatory being Social Security, Medicare, unemployment insurance, etc.). In June 2008, benefits as a percent of total hourly compensation among private-sector RNs (table

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[35] Hirsch and Schumacher (1998) show that the standard result of union wage gaps declining with education is due largely to two-sided selection into union status; that is, positive (negative) selection among those with low (high) education. To the extent that union representation produces premiums for nurses, this helps explain the finding of wage rates above long-run opportunity costs. Using our unweighted RN sample, among whom 17.1% are members, we obtain an estimated .07 log point union premium from a wage equation including membership, hospital employment, and the CPS variables in our base specification.

27, p. 285) measured 25.9%–$11.50 in benefits, $32.90 in wages and salaries, and $44.40 in compensation. For all full-time private-sector workers the corresponding figure is 27.2% of compensation—$8.26 in benefits, $22.16 in wages and salaries, and $30.42 in compensation (table 19, p. 224).[36] Based on these figures, it is fair to conclude that benefits as a percent of total compensation are somewhat lower for RNs than for comparable (e.g., college-educated) workers and jobs economy-wide.[37] If anything, our estimates of the RN wage gap are likely to slightly overstate the compensation gap.

An issue not formally addressed in this article is the difference in timing of work. Healthcare workers are more likely to work weekends and nonstandard shifts. A BLS newsletter (U.S. BLS 2008b) reports that healthcare workers are more likely to work on weekends and holidays than are workers economy-wide. Using information from the 2003–2007 American Time Use Surveys they report that on a given weekday, 80% of full-time healthcare practitioner and technical workers (a category that includes RNs) are working, compared to 88.1% of workers in non-health occupations. On holidays and weekends, 35.1% of the health employees are working, compared to 31.2% of non-health employees.

Failure to account for timing of work is likely to bias upward estimates of the RN wage gap.[38] It is difficult to "price" time of work differentials owing to selection into workdays and shifts selection (e.g., Kostiuk 1990). We construct a rough back-of-the-envelope estimate. Schumacher and Hirsch (1997) examine differences in earnings for RNs from shift work. Based on the May 1985 and 1991 CPS Dual Job Supplements, they find that 57% of RNs work day shifts, with others split between night, evening, rotating or split, and other shifts. Relative to a day shift, they estimate differentials for night work of 11% and differentials for the other shifts of about 4%. Assume that such scheduling and shift differentials for RNs hold today (they may be lower, given decreased RN employment in hospitals). Published information from the May 2004 CPS supplement on flexible and shift schedules provides recent data for full-time workers economy-wide. As compared to the 57% of RNs who have day schedules, the economy-wide figure is 85%. Based on the differences between RNs and workers economy-wide for each shift category, coupled with the wage differential estimates by Hirsch and Schumacher, we calculate that the RN wage differential would be .018 log points lower if adjusted for shift work.[39] Although this is a rough estimate, it reinforces our conclusion that relative pay among nurses is overstated by standard wage regression analysis and is closer to opportunity costs than indicated by standard analysis.

9. Interpretation and Conclusions: Can the Shortage Puzzle Be Resolved?

Our principal finding is that wage differences between RNs and similar workers and jobs economy-wide are substantially smaller than implied by standard log wage gap estimates in the literature, on the order of 15% or less, as opposed to the 40% indicated by standard

[36] The ECEC includes supplemental pay (e.g., overtime and shift pay) as benefits. The figures shown in the text subtract supplemental pay from benefits and add them to wages and salary. Absent the shift of supplemental pay, benefits as a percentage of total compensation are 29.5% for RNs and 30.5% for full-time private-sector workers. The private-sector comparison is used since the full-time/part-time breakdown is not otherwise provided.

[37] This conclusion is consistent with results presented in McHugh et al. (2011) showing that a low level of benefits (particularly pension benefits) was a particularly strong source for job dissatisfaction among nurses in four states.

[38] Shift work is not directly measured in O*NET, although it may be correlated with measured job attributes.

[39] The details of this calculation are available on request.

analysis.[40] Two principal reasons lead to this result. First, the RN occupation requires unusually high skill levels, as compared to typical jobs populated by workers with similar levels of schooling, skill requirements and tasks not fully reflected in the CPS or other household data. In addition, nursing jobs involve more difficult working conditions than do most jobs filled by college-educated workers. Controlling for occupational attributes sharply reduces estimates of the RN wage advantage. Second, Mincerian regression log wage gaps estimated by OLS substantially overstate the percentage wage gaps among nurses owing to a substantially more compressed wage distribution among RNs than among any broad-based comparison group. Using three alternative procedures to estimate percentage differentials, we obtain estimates showing much smaller nursing wage differentials. A third estimation issue—the treatment of gender—turns out to be relatively unimportant once one provides a rich set of controls for job skill/task requirements and working conditions.

We conclude that RNs receive wages moderately but not vastly greater than opportunity costs. This conclusion sharply reduces, but does not eliminate, the nursing shortage puzzle. How can one explain high vacancy rates and shortages if RN wage rates, on average, are moderately above opportunity costs? Although answering such a question with a formal analysis is beyond the scope of our article, we believe that reasoned argument coupled with evidence points us in the right direction.

We rule out a monopsony explanation for the puzzle since, contrary to evidence, it implies wages below rather than above competitive levels. More convincing explanations for shortages, we would suggest, should focus on adjustment difficulties on the demand and supply sides of the market.[41] Such explanations can account for high vacancy rates despite wages above opportunity cost. Perhaps most important, entry into the nursing profession is constrained, with available training slots below the number of qualified applicants. Constraints on nursing program enrollments stem from several sources, but key factors are the limited growth in nursing education opportunities (relative to demand) and the difficulty in hiring qualified nursing faculty at the salary levels funded by educational institutions (e.g., Spetz and Given 2003; Rahn and Wartman 2007; Aiken and Cheung 2008). The American Association of Colleges of Nursing (2009) reports increasing enrollments (but at declining rates of increase) during the 2000s, with record numbers of qualified applicants turned away from baccalaureate programs—29.4, 37.5, 38.4, 36.4, and 41.4 thousand during the 2004–2008 time period. A shortage of nursing faculty is the primary reason cited for rejecting applicants. These "turn-away" figures can be compared to the 63.3 thousand BA nursing degrees conferred in the 2007–2008 academic year (Snyder and Dillow 2010 [table 275]).[42]

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[40] Our 2005–2008 sample period was a time of relatively high RN wages. Using CPS data, the ratio of mean RN wages to female wages economy-wide was relatively constant over the years 2003–2009 (it declined in 2010) but about 4 percentage points higher than in 1997–2002. Had our analysis been performed for these earlier (or possibly future) years, we would likely find RN wages closer to long-run opportunity costs.

[41] Long, Goldfarb, and Goldfarb (2008) develop models in which "economic" and "professional standards" shortages can result. One model focuses on the choice between hiring permanent staff nurses and temporary contract nurses. A second posits hospitals as "premier" or "funds-constrained" and shows that the type of shortage can vary with type of hospital.

[42] U.S.-educated first-time pass rates on NCLEX-RN licensing exams were 88.4% in 2009 (National Council of State Boards of Nursing 2010). If incremental admittees were to have similar pass rates, newly licensed RNs would increase proportionally to the increases in program admissions. The 2009 federal stimulus bill (the American Recovery and Reinvestment Act) provides funding for nurse training and instruction (Domrose 2009). The 2010 health care reform legislation (the Patient Protection and Affordable Care Act, as amended by the Health Care and Education Reconciliation Act) addresses projected shortages and retention of nurses by increasing the capacity for education, supporting training programs, providing loan repayment and retention grants, and creating a career ladder to nursing (Kaiser Family Foundation 2010).

Nursing supply constraints produce relatively inelastic short-run RN labor supply curves, with short-run market-clearing wages well above the long-run opportunity costs measured by our wage analysis. Because there has been rising demand for nurses over time and because hospital budgets are constrained and adjust with considerable lags, nursing wages can be above opportunity costs and at the same time below short-run market-clearing levels. In short, institutional constraints on nurse training likely lead to shortages coexisting with wages moderately above long-run opportunity costs.[43] While the supply constraint in training can explain wage advantages for RNs compared to other college-educated workers, we show that the size of the wage advantage is not nearly as large as standard analysis indicates.[44]

An additional supply explanation is that labor supply among nurses, particularly married women, appears to be countercyclical (Buerhaus 1993; Buerhaus, Staiger, and Auerbach 2003). Such changes in labor force participation will be exacerbated, if not create periodic shortages, during high-demand periods, while working in the opposite direction during low-demand periods. Evidence during the recent economic downturn supports this argument (Evans 2009; RWJF 2009). Such a pattern should be stronger the more positively correlated is hospital (and other health-industry) demand with the national economy.

Our evidence shows that RNs are neither "underpaid" nor substantially "overpaid" as implied by standard wage analyses. Although important data and methodological issues accompany all wage analyses, such issues have proven particularly important in analyzing nursing wages. Our preferred estimates of nursing wage differentials (ignoring shift work and benefits) are that average RN wages exceed long-run opportunity cost by roughly 15%, the same order of magnitude as seen for unions (Hirsch and Macpherson 2010; table 2) and professional licensing (Kleiner and Krueger 2010).

Apart from what the analysis tells us about nursing labor markets, there are two more general implications of this research. First, wage analyses can be enriched by supplementing standard worker and location attributes with job-based measures of compensable skills, job tasks, and working conditions. O*NET provides an unusually rich set of occupation-based measures. Second, the standard approach for estimating Mincerian log wage gaps can be questioned not just in the (perhaps extreme) case of nurses but whenever one compares a single occupation or "narrow" treatment group to a (generally appropriate) broad comparison group. There is no shortage of such examples in the labor economics literature.

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[43] As noted by a referee, budget lags are explained in part by reliance on third-party payments, often regulated or contractual. Supply constraints are mitigated by a supply of foreign-trained RNs. Schumacher (2011) finds that 3.3% of U.S. RNs received their nurse training outside the United States. In our (unweighted) CPS sample of RNs, 4% are foreign-born noncitizens, while an additional 6% are naturalized citizens.

[44] Although our focus is on understanding why RN wages might exceed opportunity costs, wages moderately below long-run opportunity costs be ruled out *a priori*. Monopsonistic power or funding constraints among employers combined with imperfect mobility can lead to "underpaid" nurses. Wage analysis provides little if any evidence for systematic underpayment.

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