

Choosing Skilled Foreign-Born Workers: Evaluating Alternative Methods for Allocating H-1B Work Permits*

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April 2017

Abstract

The H-1B program allows highly-educated foreign-born labor to temporarily work in the United States. Quotas restrict the number of H-1B recipients. In many years, all available work permits were allocated by random lottery. This paper argues that an alternative distribution method based upon ability would increase output, output per worker, and wages paid to less-educated workers. Baseline estimates suggest that a change in allocation policy could result in a \$26.5 billion gain for the economy over a six year period. This estimate grows when H-1B demand rises.

Key Words: Skilled Workers, H-1B Work Permit, Immigration

JEL Codes: J61, F22

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1 Introduction

Economists agree that highly-educated workers are scarce and productive inputs in the creation of macroeconomic output. The H-1B program attempts to increase the supply of highly-educated workers, and therefore output, by providing temporary work permits to foreign-born individuals in specialty occupations seeking employment in the United States. Current policy restricts the number of new H-1B permits distributed to prospective employees of most firms to 65,000 per year, plus an additional 20,000 for workers who have obtained a master's degree or higher education in the US.

The distributional consequences of this program are widely debated in the academic literature. Basic supply and demand models argue that the increased supply of educated foreign labor should reduce compensation paid to similar native-born workers. Though some empirical studies support this view, alternative work argues that immigrants instead complement native-born labor and expand employment opportunities. Policy implications of these studies inform opposing views about whether access to skilled worker permits should be expanded or contracted. This paper takes no stance on that debate: We assume that the current quota is given and fixed, and we recognize that empirical assessments of how an H-1B program expansion would affect labor market opportunities for native-born workers have been well-covered by other studies including Kerr, Kerr, and Lincoln (2015), Doran, Gelber, and Isen (2014), Ghosh, Mayda, and Ortega (2014), and Peri, Shih, and Sparber (2015a).

This paper instead focuses on *how* H-1B work permits are allocated. Two options are considered. The first operates according to recent practice in which US Citizenship and Immigration Services (USCIS) has distributed permits through a random lottery. The second is a hypothetical alternative that would award permits according to ability. Since this method is never observed, regression analysis cannot identify the costs and benefits of each system. Instead, this paper performs a calibration exercise built upon a simple theory, observed data, and prior work. The simulations demonstrate that an allocation method assigning permits according to ability – as measured by the wage and marginal product of labor associated with individual applicants – would increase macroeconomic production and output per worker regardless of the elasticities of substitution across education and nativity groups. Wages paid to workers with little educational attainment would also rise. Whether highly-educated native-born workers benefit or suffer from the alternative policy,

in contrast, does depend upon relative elasticities.

A priori, some of these implications might appear obvious: If policy is designed to allow the most productive individuals to work in the economy, then productivity will increase. Nonetheless, this calibration exercise is worth conducting for at least two reasons. First, while many people continue to debate broad immigration issues such as the expansion or contraction of the H-1B program, little attention has been paid to the effect that narrower immigration policy changes could have on the economy. Policy makers should have a sense of the economic ramifications of the current H-1B allocation method. Although one might expect that allocation favoring ability would increase output, this paper assesses how large potential gains might be. It is useful to examine potentially beneficial changes to the US immigration system beyond altering the size of flows entering the country. Second, the academic literature has developed highly-contested estimates of the elasticity of substitution between native and foreign-born workers. These estimates form the core of many debates on the consequences of immigration. This paper, in contrast, illustrates that this parameter is inconsequential for determining the average macroeconomic effects of H-1B permit allocation.

The analysis proceeds as follows: Section 2 develops the theory. It takes a restrictive view of the benefits of immigration. Recent work has argued that the H-1B program and highly-educated foreign-born workers are vital for the Science, Technology, Engineering, and Mathematics (STEM) workforce of the economy, which is in turn responsible for much of the country's technological and productivity growth. Two-thirds of H-1B workers are employed in computer-related occupations, for example. This paper's model instead restricts foreign inputs to the production of finished goods. Those workers might or might not complement native-born and less-educated workers in the production process, but the model does not permit them to generate technology spillovers. As noted above, the degree of complementarity does not affect the main productivity implications of the model, though it will influence wage effects. This section closes by outlining the mathematics behind the two allocation policies considered, and by acknowledging the limitations and simplifying assumptions of the model.

Section 3 describes the data and assumed parameters used to calibrate the model. The exercise uses data found in the US Census and American Community Survey (ACS), USCIS information acquired from a Freedom of Information Act (FOIA), and parameter estimates produced by past studies. The simulations in

Section 4 show that changing the allocation scheme from the current lottery method to one favoring the most productive workers can raise output (and output per worker) by 0.15% over a six-year period (the maximum length of time an individual can work on H-1B status, with limited exception). On the one hand, this figure appears small. On the other hand, the annual flow of 85,000 H-1B workers represents just 1.3% of foreign-born skilled employment in 2014, so the magnitude of the response is naturally limited in scope relative to the total size of the US economy. Given the context of the program's size, its magnitude is large but reasonable. Moreover, a 0.15% rise in US income represented roughly \$26.5 billion in 2014. This amounts to a level of output comparable to the entire GDP of Jamaica in purchasing power parity terms, and it exceeds the GDP of nearly 100 nations of the world. Estimates for the potential GDP gain are particularly sensitive to H-1B demand and relative permit scarcity. Using different data and parameter assumptions, figures range from \$8.3 billion when many workers who desire a permit are able to secure one, to \$43.3 billion in recent years when at most one-third of prospective H-1B applicants receive a permit.

2 Theoretical Model of Production

Recent studies have produced ample evidence that highly-educated foreign-born workers (and H-1B workers more specifically) generate technological gains. For example, Hunt (2011) argues that immigrants are more entrepreneurial and innovative than native-born workers. Hunt and Gauthier-Loiselle (2010) and Kerr and Lincoln (2010) cite the disproportionate innovative activity among immigrants in the form of patents. And Peri, Shih, and Sparber (2014, 2015b) note that skilled foreign workers specialize in STEM work responsible for much of the productivity gains in the US in recent decades.

Positive externalities associated with innovation, entrepreneurship, and technological progress imply that theoretical models incorporating foreign-born contributions to these phenomena are especially likely to find that immigration generates productivity and wage gains throughout the economy. The model in this paper, by contrast, adopts a more modest view with the aim of developing conservative estimates of foreign-born contributions to aggregate output, output per worker, and wages. Thus, the model underlying the analysis in this paper allows workers to enter the production function directly without causing spillovers.

2.1 Model with Homogenous Foreign Skills

Suppose aggregate output (Y) is produced by using two intermediate goods: Y_L is a good produced using low-education labor, and Y_H is produced using high-education labor. These two inputs are imperfectly substitutable according to the elasticity $\sigma \in (0, \infty)$. The relative productivity of Y_L and Y_H are captured by $\beta_Y \in (0, 1)$ and $(1 - \beta_Y)$. These intermediate goods combine to form final output¹ according to Equation (1).

$$Y = \left(\beta_Y \cdot Y_L^{\frac{\sigma-1}{\sigma}} + (1 - \beta_Y) \cdot Y_H^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \quad (1)$$

Let us assume that Y_L is produced by low-education labor only, which supplies labor inelastically. This input is homogenous, implying that $Y_L = L$, the total low-education labor supply. The good produced by high-education labor is more nuanced. This process uses highly-educated native workers (N) and a composite measure of educated foreign-born labor supply (Y_F). Educated native and foreign-born groups might be differentiated from each other and complementary in some way. For example, Peri and Sparber (2011) document a comparative advantage among highly-educated workers in which foreign-born workers specialize in quantitative and analytical skills, whereas natives specialize in communication skills. The model is agnostic about the exact mechanism through which complementarities occur, and is indeed agnostic about whether such complementarities exist at all. It merely allows for the possibility of complementarities that directly enter into the production function without generating technology (or other) spillovers. These inputs produce good Y_H according to Equation (2).

$$Y_H = \left(\beta_H \cdot N^{\frac{\theta-1}{\theta}} + (1 - \beta_H) \cdot Y_F^{\frac{\theta-1}{\theta}} \right)^{\frac{\theta}{\theta-1}} \quad (2)$$

Similar to above, $\theta \in (0, \infty)$ measures the elasticity of substitution between highly-educated native and foreign-born workers (or more specifically, a composite of educated foreign-labor contributions governed by Y_F). $\beta_H \in (0, 1)$ and $(1 - \beta_H)$ describe their relative productivity. Individuals again supply labor inelastically so that N and F are the total supply of native and foreign-born labor with high levels of education. For

¹One could multiply this production function by a constant and exogenous level of technology. Such an augmentation would be consistent with Clemens's (2013) evidence on the role of location-specific inputs to production (e.g., geography, institutions, and agglomeration economies) in generating wage gains for H-1B workers. Introducing this factor to the model would not, however, affect estimates of the percentage differences in wages or output due to the policy alternatives examined in this paper.

now, let us assume that foreign-born labor is homogenous in nature so that Y_F and F are equivalent.

If markets are competitive and workers are paid a wage (w) equal to their marginal product of labor, then the first derivative of the production function identifies equilibrium wages:

$$w_L = \beta_Y \cdot \left(\frac{Y}{L}\right)^{\frac{1}{\sigma}} \quad (3)$$

$$w_N = (1 - \beta_Y) \cdot \beta_H \cdot \left(\frac{Y}{Y_H}\right)^{\frac{1}{\sigma}} \cdot \left(\frac{Y_H}{N}\right)^{\frac{1}{\theta}} \quad (4)$$

$$w_F = (1 - \beta_Y) \cdot (1 - \beta_H) \cdot \left(\frac{Y}{Y_H}\right)^{\frac{1}{\sigma}} \cdot \left(\frac{Y_H}{F}\right)^{\frac{1}{\theta}} \quad (5)$$

The production function is homogenous of degree one in the inputs L , N , and $Y_F = F$. Each factor J 's share of income is easily computed as $\frac{w_J \cdot J}{Y}$, which also represents the elasticity of Y with respect to J , $\frac{d \ln(Y)}{d \ln(J)}$. Thus, the parameters $\lambda = \frac{d \ln(Y)}{d \ln(L)}$, $\eta = \frac{d \ln(Y)}{d \ln(N)}$, and $\phi = \frac{d \ln(Y)}{d \ln(Y_F)} = \frac{d \ln(Y)}{d \ln(F)}$ are the income shares paid to less-educated labor, highly-educated natives, and highly-educated foreign workers, respectively. Their values sum to one. Importantly, the last of these income shares is also an expression of educated foreign labor's effect on output, which is incorporated into other effects experienced in the economy:

$$\frac{d \ln(Y)}{d \ln(Y_F)} = \phi \quad (6)$$

All wages are positive but decreasing in the supply of own-group labor. More interestingly, the effect of high-education foreign labor on low-education and native-born high-education workers is governed by:

$$\frac{d \ln(w_L)}{d \ln(Y_F)} = \frac{1}{\sigma} \cdot \frac{d \ln(Y)}{d \ln(Y_F)} = \frac{\phi}{\sigma} \quad (7)$$

$$\begin{aligned} \frac{d \ln(w_N)}{d \ln(Y_F)} &= \frac{1}{\sigma} \cdot \left(\frac{d \ln(Y)}{d \ln(Y_F)} - \frac{d \ln(Y_H)}{d \ln(Y_F)} \right) + \frac{1}{\theta} \cdot \left(\frac{d \ln(Y_H)}{d \ln(Y_F)} \right) \\ &= \frac{1}{\sigma} \cdot \left(\phi - \frac{\phi}{1 - \lambda} \right) + \frac{1}{\theta} \cdot \left(\frac{\phi}{1 - \lambda} \right) \\ &= \left(\frac{\phi}{1 - \lambda} \right) \cdot \left(\frac{1}{\theta} - \frac{\lambda}{\sigma} \right) \end{aligned} \quad (8)$$

Note three implications of the model: First, Equation (7) clearly demonstrates that wages paid to less-educated workers are strictly increasing in the number of highly-educated foreign-born workers in the market. Second, foreign labor flows benefit low-education workers more than high-education natives if $\sigma < \theta$. That is, if high and low education labor are less substitutable than native and foreign-born labor within education groups. This arises because $\frac{d \ln(\frac{w_N}{w_F})}{d \ln(F)} = (\frac{1}{\theta} - \frac{1}{\sigma}) \cdot \frac{d \ln(Y_H)}{d \ln(F)}$. Given that estimates in the literature place σ at or below two and all values of θ above four, this inequality is likely to hold. Section 3.3 will discuss values of these elasticities more extensively. Third, effects on wages paid to highly-educated native-born workers are ambiguous. Although the relative wage paid to native versus foreign-born workers is always increasing in F since $\frac{d \ln(\frac{w_N}{w_F})}{d \ln(F)} = \frac{1}{\theta} > 0$, absolute wages of highly-educated natives rise only if $\frac{\sigma}{\lambda} > \theta$. This will ultimately be the same condition that governs whether a policy change from random to ability-based admission of foreign workers into the US economy would benefit or harm highly-educated native workers.

There are two intuitive approaches to interpreting this inequality. The first is to consider each elasticity in the expression separately. Highly-educated foreign-born workers increase wages of similar native-born workers if high and low education employees are highly substitutable (σ is high), native and foreign-born workers are highly complementary (θ is low), or if the elasticity of output with respect to low education workers (λ) is low (implying that high education workers contribute more to aggregate output). The second interpretation begins by recognizing that $\frac{\sigma}{\lambda}$ represents the elasticity of demand for highly-educated workers. Thus, skilled foreign labor will increase highly-educated natives' wages only if the elasticity of demand is greater than the elasticity of substitution between nativity groups.

One advantage of this latter interpretation is that labor demand elasticity facilitates comparison to the theory and calibration exercise in Bound et al. (2015). They implement a partial equilibrium model to assess how labor demand shocks affected the market for computer scientists in the United States beginning in the late 1990s. They assume that native and foreign labor are close substitutes, and find that the effect of immigration on computer scientists “depends crucially on the elasticity of demand for their services” (page S190). Motivated by elasticity estimates in Ryoo and Rosen (2004) and Borjas (2009), Bound et al. (2015) allow the demand elasticity to vary from 1.3 to 4.0, finding that less elastic demand is associated with worse outcomes for natives. Although the interest in this paper is not in demand shocks but rather to

measure responses to the compositional change in immigrant supply, predictions of the models are similar. Inelastic demand (low values of $\frac{\sigma}{\lambda}$) does imply that skilled immigrants will cause wage losses for skilled natives in Equation (8), though complementarities can offset this effect. As mentioned above, Section 3.3 will thoroughly discuss parameter values used in the calibration. As a preview to that discussion, we simply note now that we will prefer values of $\sigma = 1.75$ and $\lambda = 0.56$, implying an elasticity of skilled labor demand equal to 3.125 that falls in the range of Bound et al.’s (2015) elasticities of demand for computer scientists. This value is much smaller than usual estimates for the elasticity of substitution between native and foreign labor.

2.2 Model with Heterogenous Foreign Skills

Now relax the assumption of homogenous skills among educated foreign workers.² Suppose that a highly-educated foreign worker (i) is associated with a quality adjuster $q_i \in (0, \infty)$ of mean value equal to one. This parameter captures a foreign-born worker’s ability beyond educational attainment. Without loss of generality, suppose workers are ordered from highest to lowest ability. Then the composite input of educated foreign-born workers becomes $Y_F = \sum_{i=1}^F q_i$, and the high-education intermediate good is produced according to Equation (9).

$$Y_H = \left(\beta_H \cdot N^{\frac{\theta-1}{\theta}} + (1 - \beta_H) \cdot \left(\sum_{i=1}^F q_i \right)^{\frac{\theta-1}{\theta}} \right)^{\frac{\theta}{\theta-1}} \quad (9)$$

Note that $\sum_{i=1}^F q_i = F$ due to the assumed mean of q_i equal to one. Furthermore, Equation (9) encompasses the case of homogenous educated foreign-labor in the event that all $q_i = 1$.

The principal difference with heterogenous foreign-labor is that the wage paid to worker i is scaled by the value of his or her ability q_i as in Equation (10) below. Not only does this equation identify productivity consequences of hiring worker i , but it carries pragmatic significance as well: It argues that if workers are paid their marginal product of labor, higher ability workers can be identified through their wages. In other words, the highest ability candidates in a pool of H-1B applicants will be those individuals who have received

²Hunt (2015) identifies a number of reasons why productivity might vary including differences language proficiency, college degree field, and occupation.

the largest wage offers.

$$w_{F_i} = q_i \cdot (1 - \beta_Y) \cdot (1 - \beta_H) \cdot \left(\frac{Y}{Y_H}\right)^{\frac{1}{\sigma}} \cdot \left(\frac{Y_H}{F}\right)^{\frac{1}{\theta}} \quad (10)$$

The heterogenous model in (9) does not alter the wage functions for less-educated workers or highly-educated natives expressed in (3) and (4).³ The share of income paid to heterogenous foreign labor remains $\phi = \frac{d \ln(Y)}{d \ln(Y_F)}$, but the addition of an F^{th} worker of quality q_F implies $\frac{d \ln(Y)}{d \ln(F)} = \frac{d \ln(Y)}{d \ln(Y_F)} \cdot \frac{d \ln(Y_F)}{d \ln(F)} = \phi \cdot q_F$. This expression is incorporated into the wage effects for less-educated and highly-educated native-born workers ($\frac{d \ln(w_L)}{d \ln(F)}$ and $\frac{d \ln(w_N)}{d \ln(F)}$). Thus, the addition of a foreign worker of quality q_i alters the output of the good produced by highly-educated labor, the highly-educated native-born worker wage, and the wages paid to less-educated labor by a factor of q_i relative to the average effect (i.e., the effect from a one-unit increase in homogenous labor unit F). However, elasticities with respect to the composite input Y_F expressed in equations (7) and (8) are unaltered. These expressions, which remain a function of highly-educated foreign-labor's share of income (ϕ), are central to calibration exercises examining the wage implications of alternative H-1B allocation policies.

The model could introduce heterogeneous native skilled labor as well, but this would have minimal effect on the main predictions. Heterogeneous native labor would cause w_N to be scaled according to ability much as with the case of foreign labor. However, this change would have no consequence for $\frac{d \ln(w_N)}{d \ln(Y_F)}$ or $\frac{d \ln(Y)}{d \ln(Y_F)}$. In essence, the heterogeneity of foreign skills is important because immigration policy can be altered to effectively choose which workers enter the country. Since native labor is inelastically supplied in the full employment model of this paper, educated native-born workers are a fixed factor of production regardless if they exhibit heterogeneity or not.

2.3 Policy Alternatives

Suppose policy-makers decide to limit the number of highly-educated foreign workers it allows into the country to a fixed proportion, $\rho \in (0, 1)$, of the total number of workers (F) who would like to do so. Let us consider two alternatives for implementing this policy. Policy *A* works much like the current H-1B program and distributes work permits through a random lottery. Policy *B* achieves the same goal of immigration

³Though one might want to replace the homogenous F in the high-education input with $\sum_{i=1}^F q_i$.

reduction and admits the equivalent number of applicants by instead choosing those with the highest ability. Output of the intermediate good produced by highly-educated labor is governed by one of the two following functions:⁴

$$Y_H \equiv Y_A = \left(\beta_H \cdot N^{\frac{\theta-1}{\theta}} + (1 - \beta_H) \cdot \left(\rho \cdot \sum_{i=1}^F q_i \right)^{\frac{\theta-1}{\theta}} \right)^{\frac{\theta}{\theta-1}} \quad (11)$$

$$Y_H \equiv Y_B = \left(\beta_H \cdot N^{\frac{\theta-1}{\theta}} + (1 - \beta_H) \cdot \left(\sum_{i=1}^{\rho \cdot F} q_i \right)^{\frac{\theta-1}{\theta}} \right)^{\frac{\theta}{\theta-1}} \quad (12)$$

Output and less-educated workers both benefit from the policy that generates higher levels of Y_H since both final output (Y) and wages paid to less-educated labor (w_L) are unambiguously increasing in Y_H . Output per worker also rises since the number of workers is equivalent in the two scenarios.

Expression (11) arising from Policy *A* effectively comes from the expected value of foreign-labor contributions. Each worker i has an equal probability ρ of receiving a work permit. Since no selection of $\rho \cdot F$ workers can result in a higher level of total skill supply than the selection of the best $\rho \cdot F$ workers implied by Expression (12) and Policy *B*, we know that $Y_B > Y_A$. More formally, it can be shown that $Y_B > Y_A$ if $\sum_{i=1}^{\rho \cdot F} q_i > \rho \cdot \sum_{i=1}^F q_i$. That is, if the total ability of the best $\rho \cdot F$ workers exceeds $\rho\%$ of the ability of all possible workers. The concave nature $\sum_{i=1}^F q_i$ that arises due to the ordering of individuals guarantees that this result holds. The Appendix provides a more formal illustration of this result.

2.4 Model Caveats

The model adopts a number of simplifying assumptions. For example, as a full employment model with inelastic labor supply, evaluation of policy alternatives will abstract away from potential unemployment spells; native exit from the labor market; native displacement into other sectors, areas of study, or occupational skills less prone to competition with foreign labor; the possible existence of skills shortages; and business cycle fluctuations. Similarly, it does not include a role for asymmetric bargaining power between employers and prospective foreign workers, increased search costs associated with hiring immigrant labor, or multiple methods of foreign entry to the US labor market. These are all areas of important concern within

⁴Policy *A* results in a probabilistic outcome. We present output resulting from expected values.

immigration debates.

Incorporation of some of these issues would dampen potential gains from immigration policy changes. Elastic native labor supply, for example, would imply that employment would not rise by the full amount of a positive immigration shock. This muted increase in a factor of production would lessen predicted GDP responses.

Conversely, incorporation of other issues could boost potential gains. For example, critics of the H-1B program sometimes argue that it amounts to an indentured servitude scheme since H-1B workers must exit the US if they become unemployed.⁵ This implies that firms might possess a degree of market power that could vary across permit allocation methods. Despite the existence of a wage floor for H-1B workers (discussed in more detail in Section 3.3), lottery allocation could facilitate firms' efforts to underpay H-1B employees threatened by deportation during an unemployment spell precipitated by a job search. Under an allocation method that awards permits to the individuals earning the highest wage (a proxy for ability), in contrast, sponsoring firms have increased incentive to accurately report their willingness to pay for foreign labor, and thus help ensure that foreign labor cannot be used to undermine native-born workers.

These issues are undoubtedly important. Nonetheless, this paper conducts a calibration exercise to provide baseline estimates of GDP and wage consequences of H-1B allocation policy under a more simplified setting. In doing so, it should provide a starting point for discussions about how immigration permits are distributed.

3 Data and Model Parameterization

Section 2 outlined the basic theory underlying two methods for allocating H-1B permits to highly-educated foreign-born workers. The currently-employed method of distributing permits by random lottery will result in lost output, output per worker, and wages paid to less-educated workers when compared to a process of allocating permits to the highest ability foreign-born workers. The magnitudes of these effects depend upon parameters driving the model. Simulation will help to understand these effects better. This section describes the data and parameters from the US Census (acquired from Ruggles et al., 2015), ACS, USCIS (acquired

⁵See concerns expressed in Hira (2010), Matloff (2008, 2013), and Miano (2007), for example. Depew, Norlander, and Sorensen (2017), and Sparber (2015) offer counter-evidence.

from a FOIA), and past work that will form the basis of that exercise.

Ultimately, we are interested in the changes of output (Y), less-educated workers' wages (w_L), and highly-educated native-born workers' wages (w_N) caused by a change in the value of the composite input of high education foreign-born workers (Y_F). These expressions were derived in Equations (6)-(8). They are fully governed by the income shares λ , η , and ϕ , and the elasticities of substitution between education groups (σ) and between highly-educated native and foreign-born workers (θ). Values for changes in Y_F implied by the different H-1B allocation schemes require estimates of the quality of foreign-born workers (q) – as determined by the underlying distribution of workers seeking an H-1B permit – and the proportion of foreign individuals seeking a work permit who successfully acquire one (ρ).

3.1 H-1B Data and the Skills of Foreign Workers

Values for ρ and q can be gleaned from USCIS information but will vary depending upon the year used to construct the parameters due to both changing H-1B demand and the evolution of the program.

3.1.1 Calculation of ρ

Limits on the number of new H-1B issuances per year have fluctuated over time. The quota for new H-1B issuances in fiscal year 2000 (October 1999 – September 2000) was 115,000. Though the cap was reached six months prior to the end of the fiscal year (in March), USCIS received applications for new H-1B permits throughout that year because Congress acted to temporarily raise the annual cap to 195,000 for fiscal years 2001-2003. When that temporary limit expired, the quota was reduced to 65,000 for fiscal year 2004. Beginning in fiscal year 2005, an additional 20,000 permits have been available to workers with an advanced degree from US universities. Employees of colleges, universities, and non-profit research institutions are exempt from this cap, as are workers who renew their H-1B status for continued work with enterprises otherwise subject to H-1B limits (for example, for-profit firms).

Although firms seeking to hire an H-1B worker must file a Labor Condition Application (LCA) attesting that they will comply with the requirements of the H-1B program, they submit many more LCAs than the number of workers they intend to hire. Moreover, H-1B permits are awarded to individuals, not firms.

Therefore, the most reliable data on H-1B workers comes from I-129 applications for H-1B status, which we acquired through a FOIA.

In principal, US Citizenship and Immigration Services (USCIS) distributes cap-bound H-1B work permits according to a first-come / first-served basis. However, I-129 applications for fiscal years 2008, 2009, and 2014 through 2017 exceeded the number of available permits during the first week of eligibility. USCIS responded by conducting a random lottery to assign all H-1Bs in those years. Unfortunately, this implies that we cannot observe the pool of potential H-1B applicants, nor do we know how big that pool is – there is no reason to apply after the available permits have been distributed. Thus, it is impossible to know the true value of the desired number of permits (F), the probability of securing one (ρ), and the skill distribution of potential applicants.

The calibration exercise will focus on three potential values of ρ . First, applications in calendar year 2000 (for presumptive fiscal year 2001) provide the cleanest measure of the pool and skill distribution of workers seeking H-1B status in a year of high labor demand. Though an H-1B cap existed in that year, it was not binding: According to our sample selection criteria (described in more detail in the next subsection), 141,178 foreign workers applied for and received a cap-dependent H-1B permit. If the cap had been set at 65,000 in that year, it would have implied that $\rho = 0.46$.

Second, 2001 might seem like a better year for calibrating the value of ρ since the H-1B cap was high and non-binding throughout the calendar year. However, declining cyclical GDP and the events of September 11 combined to reduce H-1B demand, leading to a hypothetical value of $\rho = 0.77$. This observation points to an important regularity: The value of ρ , which cannot be measured in the current policy environment, will be lower in years with higher latent H-1B demand.

Third, desire for a cap-bound H-1B permit has been exceedingly large in recent years. USCIS (2015, 2016) reports having received 233,000 applications from foreign workers in the first week of application eligibility for fiscal year 2016, and 236,000 applications during the first week for fiscal year 2017. Even with 85,000 permits now available, this implies a maximum value of $\rho = 0.36$ that would be lower if additional foreign workers had hoped to apply for a permit later in the year.

3.1.2 Estimating the Skill Distribution and Skill Supply of H-1B Workers

The skill supply of H-1B workers will differ across Policies A and B . The calculation of H-1B skill supply under Policy A is straightforward. Recall the relationship between q_i and wages derived above. The assumed mean of $q_i = 1$ reflects a normalization of individual wages such that $q_i = \frac{w_{F_i}}{\bar{w}_F}$, where \bar{w}_F is the average wage paid to highly-educated foreign workers. If we allow F to represent the total number of workers seeking an H-1B, and recalling that $\frac{1}{F} \sum_{i=1}^F q_i = 1$ is the average value of q , then Policy A implies that the value of $Y_F = \rho \cdot F = 65,000$ by construction (or 85,000 if the additional permits for US-educated advanced degree workers are included).

The H-1B skill supply under Policy B , in contrast, depends upon the distribution of foreign ability. Again, USCIS data is informative. The analysis relies upon the skill distribution, based upon wages paid to H-1B workers, in two separate years.

First, baseline estimates will rely on new H-1B applications subject to the H-1B cap in 2000. As noted, H-1B demand was high in this year, but caps were not binding, so the entire distribution of prospective H-1B workers can be observed. Our data removes individuals who are exempt from H-1B caps (such as those renewing their H-1B status and/or employees of non-profit research institutions). We also retain only those individuals earning a (nominal) annual wage between \$15,000 and \$1,000,000 so as to eliminate people at the extreme ends of the wage distribution (and who might be subject to measurement error).

The top panel of Figure 1 plots the resulting histogram of the ability distribution of the 114,178 workers applying for an H-1B permit in 2000 in the resulting dataset. The values of q_i approximate a log-normal distribution but with heavy skewness to the right. Bars shaded in blue reflect the individuals among the top 65,000 wage earners who would be included in the Policy B construction of Y_F . The summed skills of these top 65,000 workers equals 82,270, thus implying a much greater production input than the expected value generated by the lottery.

The ability distribution in 2000 could be quite different from the pool of more recent applicants. Not only could there have been structural changes in the US economy, but patterns in applications for H-1B permits may have changed. For example, H-1B applications for fiscal years 2008, 2009, and 2014 through 2017 exceeded the number of available permits during the first week in which prospective workers could apply

(in April of the preceding calendar year). If workers from specific occupations and source countries are more likely to apply in April than during later points in the year, it could alter the observable skill distribution of H-1B recipients. The same would be true if H-1B dependent firms or industries are particularly active in recruiting foreign labor in April.

Unfortunately – and as discussed above – the exhaustion of available permits in April implies that the full pool of prospective H-1B workers is unobservable. Nonetheless, it is important to assess whether the main calibration results are robust to alternative skill distributions. To do so, we use the distribution of cap-bound H-1B recipients for fiscal year 2009. This is the last year in our available data in which all cap-bound permits were distributed by lottery (which was conducted among the applications received in the first week of April 2008). If H-1B allocation was random, then the observed sample of H-1B recipients should be representative of H-1B applicants during that week. Therefore, cap-bound H-1Bs awarded in April 2008 can serve as a measure of a more recent skill distribution.

The bottom panel of Figure 1 displays the ability histogram of these workers, using the same selection criteria as for the 2000 distribution. The histogram still displays an approximate log-normal distribution with right skewness, but now exhibits a spike at a nominal wage of \$60,000. This arises due to a disproportionate number of computer-related jobs filled in the first week of April at that wage, indicating that the evolution of the H-1B program over time might have affected the distribution of potential employees.

The shading of the diagram represents another hypothetical. Suppose the distribution was scaled up to represent a population of 236,000 prospective applicants recorded in the first week of April 2016, and further assume 85,000 available permits for the following fiscal year 2017. Then the blue shaded area represents the workers who would be selected into the labor market according to ability. Whereas random selection results in a skill supply value of 85,000 by construction, this alternative allocation method would result in a skill supply of 113,074 equivalent workers.

Appendix Table 1 provides summary statistics for log-wages (converted to real 2010 terms) for workers in both of these samples. Average wages paid to cap-bound workers were 16.9% higher in 2008 than in 2000, possibly reflecting that highly sought-after workers are more likely to apply in the first week of eligibility than throughout the year. Both figures are lower than wages paid to cap-exempt workers in those years.

This could reflect higher wages from experience since H-1B renewals do not count toward the cap. Cap-bound H-1B workers are paid more than both college-educated foreign-born and native-born workers on average, according to Census and ACS data. The table also provides summary log-wage statistics for subsets of cap-bound groups including major source countries (India, China, and the Philippines account for over two-thirds of the samples) and occupations (computer-related workers alone account for two-thirds of the sample in both years).

3.1.3 Estimating Foreign Skill Supply

The basic theory and Equations (11) and (12) assume all foreign workers reside in the country through either Policy A 's or B 's governance of the H-1B program. This is an unreasonably extreme assumption for the purpose of calibration. Many highly-educated foreign-born individuals in the United States have a long-established residence in the country and would not have been subject to current H-1B policy restrictions. Similarly, they may have entered the US through programs not considered here.

A more reasonable approach for calibrating the model would be to instead assume that $\rho \cdot \sum_{i=1}^F q_i$ and $\sum_{i=1}^{\rho \cdot F} q_i$ represent *changes* to the stock of college-educated foreign-born labor under different policy regimes. In other words, it would be appropriate to adjust the measure of Y_F by a constant factor representing foreign workers who are not (or were not) affected by the policy in question.

To accomplish this task, first define \hat{F} as a measured stock of educated foreign workers in the economy. Since Policy A currently governs US migration, assume that $Y_F^A = \hat{F}$. Second, let us assume that in a single year, the change in this stock value ($\Delta \hat{F}$) grew according to Policy A such that $\Delta \hat{F}_A = \rho \cdot \sum_{i=1}^F q_i$. If Policy B had instead been in place, this stock would have grown by $\Delta \hat{F}_B = \sum_{i=1}^{\rho \cdot F} q_i$. Third, note that individuals can work on H-1B status for a maximum of six years.⁶ If all H-1B workers had stayed in the US for this period, then the level of foreign skills that the economy could have obtained under this alternative policy equals $\hat{F} + 6 \cdot \left(\sum_{i=1}^{\rho \cdot F} q_i - \rho \cdot \sum_{i=1}^F q_i \right)$. Altogether, this implies that Equation (13) provides a comparison

⁶Exemptions to the six year limit exist. For example, Section 106 of the *American Competitiveness in the Twenty-First Century Act of 2000* allows one-year work extensions to H-1B workers for whom 365 or more days have elapsed since the filing of a PERM application or I-140 petition – steps in the process of obtaining permanent residency (a green card).

of policy proposals over a six year period.

$$d \ln(Y_F) = \ln\left(\frac{Y_F^B}{Y_F^A}\right) = \frac{\hat{F} + 6 \cdot \left(\sum_{i=1}^{\rho \cdot F} q_i - \rho \cdot \sum_{i=1}^F q_i\right)}{\hat{F}} \quad (13)$$

Given the data outlined above, one could substitute $\rho \cdot \sum_{i=1}^F q_i = 65,000$ and $\sum_{i=1}^{\rho \cdot F} q_i = 82,270$ if assuming the 2000 skill distribution and permit acquisition probability. The implied single-year skill difference due to a policy change would be $\ln\left(\frac{82,270}{65,000}\right) = 23.56\%$, but the cumulative percentage change in the stock of foreign skills over six years would depend upon the construction of \hat{F} , which depends upon data observed in the US Census and ACS. Once again, we consider alternative methods, which we discuss in the next section.

3.2 Census Data and Income Shares

The 2000 Census provides information on employment, wages, and nativity that facilitates construction of income shares. Our first method of parameterizing the model groups all workers with some college or less education into L ; native-born workers with a bachelor's degree or more education are in N ; and similarly-educated foreign-born workers are in Y_F . The data implies that income shares $\{\lambda, \eta, \phi\}$ equal $\{0.56, 0.39, 0.05\}$ and that 3,537,313 highly-educated foreign-born individuals worked in the US in 2000. Using this figure as a measure of \hat{F} and inserting it into Equation (13) implies a baseline value of $d \ln(Y_F) = 0.0289$. That is, an H-1B program allocating permits according to ability would increase the composite educated foreign labor input in production by 2.89% relative to the current program, according to 2000 Census and USCIS data. This figure will rise or fall depending upon assumptions regarding ρ and the underlying H-1B skill distribution, and will be discussed in the calibration exercise.

The choice of including the full number of educated foreign-born workers in the construction of Y_F might be an extreme assumption since larger \hat{F} values will bring the $\frac{Y_F^B}{Y_F^A}$ ratio closer to one and its log closer to zero. A second method of parameterizing the model instead measures \hat{F} using just the 769,573 workers in the 2000 Census who have resided in the US six or fewer years – the maximum number of years a person can have H-1B status in most cases. This raises baseline estimates of $d \ln(Y_F)$ to an implied 12.63% increase in the foreign

skill component of production. By removing established immigrants from the construction of Y_F , however, income shares will change as well. We adopt an assumption that established college-educated immigrants and similar natives are perfectly substitutable and therefore incorporate both into the construction of N . This changes the income shares $\{\lambda, \eta, \phi\}$ to $\{0.56, 0.43, 0.01\}$.

A robustness check of the calibration exercise will instead rely upon the 2014 ACS to construct employment levels and income shares. Although parameter values are markedly different over this 14-year horizon, model implications are robust.

3.3 Elasticities of Substitution

The final parameters needed for simulating the effects of H-1B allocation policy are the elasticities of substitution between low and high education workers (σ) and between highly-educated native and foreign-born workers (θ). We take these values from the existing economics literature.

The former elasticity is relatively non-controversial. Table 6 of Ciccone and Peri (2005) provides a helpful summary of σ from the literature with a remarkably narrow range values spanning from 1.31 to 2.00, with higher values implying greater substitutability across education groups.⁷ In the context of this paper’s model, the effects of σ are purely distributional. Low values imply that the gains from increased highly-educated foreign-labor skills dissipate to complementary low-education labor. High values increase the likelihood of positive wage effects for educated native-born workers.

The elasticity of substitution across nativity groups, in contrast, is controversial. If the H-1B program were structured in a way that allows employers to hire foreign workers only when they cannot find an American worker, then the true elasticity of substitution (θ) should be zero. There are two reasons we should not expect this value, however. First, this is not the legal threshold for hiring an H-1B worker. The United States Department of Labor (2016) adds to the confusion over this issue. Its website claims that “The intent of the H-1B provisions is to help employers who cannot otherwise obtain needed business skills and abilities from the U.S. workforce by authorizing the temporary employment of qualified individuals who are not otherwise authorized to work in the United States.” However, it goes on to provide the more accurate

⁷Cited sources include Johnson (1970), Fallon and Layard (1975), Katz and Murphy (1992), Angrist (1995), Murphy, Riddle, and Romer (1998), Krusell et al. (2000), and Caselli and Coleman (2000).

threshold that “Employers must attest to the Department of Labor that they will pay wages to the H-1B nonimmigrant workers that are at least equal to the actual wage paid by the employer to other workers with similar experience and qualifications for the job in question, or the prevailing wage for the occupation in the area of intended employment – whichever is greater.” Firms employing a large proportion of H-1B workers in relation to their overall workforce and therefore deemed to be “H-1B Dependent” are required to make additional attestations, though exemptions for that rule also exist.⁸ Nonetheless, such restrictions do not imply that $\theta = 0$.

Second, no reliable economics study estimates that native and foreign workers are perfect complements. Card (2009, p. 17) provides a succinct summary arguing that “both the time series and cross-city evidence are consistent with a small but detectable degree of imperfect substitution between immigrants and natives.” He finds a value of θ near 40 for less-educated workers and a value near 17 among college-educated workers.

More extensive work is available from a series of papers in the February 2012 issue of the *Journal of the European Economic Association*, which also provides great insight into challenges estimating this parameter. Manacorda, Manning, and Wadsworth (2012) produce estimates suggesting the strongest complementarities. Using short-run data from the United Kingdom, their baseline estimates find $\theta = 7.8$. When estimated using recent immigrants only, the level of complementarity grows (and the parameter shrinks) to $\theta = 4.6$. University graduates exhibit a value of $\theta = 5.7$.

Ottaviano and Peri (2012) use long-run US data and find evidence for complementarity but at much higher values of θ . Their preferred estimate centers around $\theta = 20$. However, estimates for the inverse elasticity among college graduates are never significantly different from zero and sometimes have the wrong sign. When converted into an elasticity, college-educated values of θ range from about 40 to 110. Manacorda, Manning, and Wadsworth (2012) provide helpful insight into these discrepancies by noting that natives and immigrants might be more substitutable in the long run than in the short run, and that this might contribute to their disparate findings.

Critics of existing estimates of the elasticity of substitution between groups include Borjas, Grogger,

⁸Data available from the Center for Immigration Studies (Griffith and North 2016) reports that nearly 3000 H-1B dependent firms filed to hire new H-1B employees in Fiscal Year 2016. Well-known H-1B Dependent firms among top H-1B users include Cognizant, Wipro, Capgemini, and Infosys. Well-known non-dependent firms among top H-1B users include Deloitte, PriceWaterhouseCoopers, Apple, and Microsoft.

and Hanson (2012) who note that results are extremely sensitive to sample selection, weighted regression techniques, variable construction, and other methodological considerations. Their estimates of θ range from a low of 18.8 to perfect substitutability ($\theta = \infty$). Dustmann and Preston (2012) argue that estimates will be biased by discrimination and accessibility issues: If new immigrants skill-downgrade and work in jobs below their skill level, models estimating the degree of competition between natives and immigrants will face a great deal of measurement error that could bias estimates against finding perfect substitutability. If immigrants upgrade the skill-level of their occupations rapidly as they become established, the disconnect between short-run estimates and long-run estimates will grow, which could explain part of the difference between the Manacorda, Manning, and Wadsworth (2012) and Ottaviano and Peri (2012) results.

In the context of this paper’s model, the consequences of θ are strictly distributional. High substitutability between educated native and foreign-born workers implies that an increase in foreign ability is likely to reduce wages paid to similar native-born workers. Our approach will take a fairly limiting view of the potential complementarities across nativity groups by adopting a baseline assumption of $\theta = 30$. Simulations will demonstrate that the model reaches asymptotic conclusions that occur rather quickly as θ grows, so the distinction between θ values of 20, 30, 40, or even larger values are relatively minor.

4 Simulation

4.1 Main Results

Table 1 displays estimated output, productivity, and wage implications of moving from the current H-1B policy – which distributes work permits via random lottery – to one in which permits are awarded to an equivalent number of the highest ability applicants. All estimates in the table assume that low and high education workers have a high degree of complementarity ($\sigma = 1.75$) but highly-educated native and foreign-born workers are highly substitutable ($\theta = 30$). Income shares $\{\lambda, \eta, \phi\}$ are set to $\{0.56, 0.39, 0.05\}$.

Column (1) displays the baseline estimates. It computes parameter values using data from the 2000 Census and H-1B applications. All college-educated foreign-born workers are included in the calculation of foreign-born income shares. As noted above, the model predicts that a change in the H-1B permit allocation

method would increase the skills supplied by new entrants by 23.56%, and the skills supplied by foreign-born workers by 2.89% over a six year period, without changing the total number of migrants. Output gains are scaled by the skilled foreign-worker income share, $d\ln(Y) = \phi \cdot d\ln(Y_F)$. This implies a 0.15% rise in GDP over a six year period. Since labor is inelastically supplied and constant, output per worker rises by an equivalent amount. Though 0.15% is a small figure, it is not trivial in absolute terms. Given the size of the US economy (\$17.46 trillion in real 2014 terms), the implied change is equivalent to \$26.5 billion, roughly the size of the entire Jamaican economy, and greater than the GDP of nearly 100 countries in the world (CIA World Factbook 2015). Moreover, it is a relatively large effect given that sizeable changes in the annual flow of H-1B skills (the top row of simulated values) have comparably small effects on the existing stock of college-educated foreign-born employment (the second row).

The increase in high-education skills leads to a 0.09% rise in wages paid to complementary less-educated workers. This translates to a low dollar amount of \$34 per worker without a four-year college degree, but these workers accounted for 71% of the US labor force in 2000 so that a large number of people benefit. Native-born workers with a bachelor’s degree or more education experience a 0.10% wage decline. The loss arises due to the assumed high substitutability between highly-educated native and foreign-born workers (relative to the substitutability across education groups), the large share of the gains paid to low education workers, and the absence of potential technology spillovers.

The remaining columns of Table 1 explore how changes in H-1B scarcity (variation in ρ) and the underlying foreign-labor skill distribution affect the productivity gap between H-1B allocation methods. Column (2) assumes a high value of $\rho = 0.77$. This figure reflects a cap of 65,000 and the H-1B applicant pool of 2001 – reduced demand implies that a higher proportion of individuals who wanted work permits would have been able to secure them. In low-demand states of the world, the difference between distributing permits to random workers versus highest ability workers is small. Column (2) demonstrates that a change in policy at a success rate of $\rho = 0.77$ reduces the H-1B skill difference between the two allocation methods to just 1.17%. This in turn reduces the output and wage consequences. The output difference between policies amounts to just \$10.74 billion, or just 40% of the baseline figure.

Column (3) assumes $\rho = 0.36$, a figure that reflects both the massive increase in H-1B applicants in the

first week of eligibility for fiscal year 2017 (to 236,000) and the modest cap increase (to 85,000 permits). Though the annual H-1B skill flow of both Policy A and B rise, the implied skill gap between policies increases to 30%, with a six-year cumulative foreign-skill difference of 4.9%. This amounts to 0.26% of GDP, or \$44.8 billion. This is the largest estimate among the simulated values.

Columns (4)-(6) repeat these assumed ρ values but instead employ the skill distribution from April 2008. The results are remarkably similar to the analogous outcomes in Columns (1)-(3). One limitation of this approach is that the average skill value will equal one by construction, regardless of year. Column (7) addresses this by using the 2008 distribution and model setup of Column (6), but normalizing skill values to the average wage of the 2000 applicant pool. This alters both the skill value associated with the 85,000 quota (resulting in an equivalency of 79,864 workers) and the alternative achievable through ability-based allocation. Ultimately, however, the implied GDP and wage effects change very little.

Figure 2 visually illustrates how H-1B scarcity and the foreign skill distribution affect the productivity gap between H-1B allocation methods. Perhaps unsurprising given the estimates in Table 1, ρ is of vital importance but the skill distribution is of little consequence. The thick blue curve represents the relation between ρ and the GDP difference assuming the 2000 skill distribution. Values at 0.36 and 0.77 are marked and are also represented in Columns (1) and (2) of Table 1. GDP differences fall precipitously as more workers who want an H-1B permit are able to secure one. In contrast, use of the April 2008 skill distribution (yellow curve) implies only modest differences in GDP gaps relative to the 2000 distribution. Values at $\rho = 0.36$ are marked and can also be found in Column (6), Panel B, of Table 2 (discussed below).

4.2 Native and Foreign-Born Substitutability

Equations (6) and (7) demonstrate that the elasticity of substitution between educated native and foreign-born workers (θ) plays no role in determining the output or low-education wage effects of H-1B allocation policy. Equation (8), in contrast, shows that θ does affect wages paid to educated natives. The consequences of this elasticity are, therefore, entirely distributional.

The assumed parameter values and function in (8) imply that the change in allocation policy would cause a change in wages paid to college-educated native-born workers that asymptotically approaches a loss

of 0.11%. The college-educated native wage effect is positive only if $\theta < 3.125 = \frac{\sigma}{\lambda}$, and is explosive as θ approaches zero. Even with the highest degree of complementarity estimated in the literature ($\theta = 4.6$ from Manacorda, Manning, and Wadsworth, 2012), the policy change would generate a 0.035% loss in wages paid to these workers. The loss grows to 0.093% under Ottaviano and Peri’s (2012) preferred value of $\theta = 20$, and grows further to 0.107% at an extreme value of $\theta = 110$. The 0.099% loss estimate at $\theta = 30$ matches the Table 1 Column (1) value after rounding error.

These results are important in the context of prior studies. First, they will exaggerate true wage losses if educated workers generate positive technological spillovers that are potentially skill-biased. Evidence for such skill-biased technological change can be found in both the growth (Acemoglu 1998, 2002; Iranzo and Peri 2009; Jones 1995) and immigration (Peri, Shih, and Sparber 2015b) literature. Second – and as noted above – the effects of θ are confined to wage outcomes for college-educated workers. While many studies have attempted to estimate the parameter, its value has no consequence for the effect of highly-educated migration flows on GDP or wages paid to workers with little educational attainment.

4.3 Income Shares and the Stock of Foreign Workers

The results in Table 1, Figure 2, and Figure 3 incorporate the full number of educated foreign-born workers into the construction of Y_F . The results in Panel A of Table 2 instead parameterize the model by including just the 769,573 workers in the 2000 Census who have resided in the US six or fewer years into the construction of \hat{F} . The remaining skilled foreign workers are instead treated as the equivalent of a college-educated native worker.

This alternative construction of the stock of educated foreign-born labor significantly raises baseline estimates (in Column 1) of $d \ln(Y_F)$ to a 12.63% increase in the foreign skill component of production. But removal of established immigrants from Y_F also causes the income shares $\{\lambda, \eta, \phi\}$ to change to $\{0.56, 0.43, 0.01\}$. The increase in the skill change and the decrease in the highly-educated foreign-born labor share of income largely offset each other. Their product implies a GDP difference between H-1B allocation policies equal to 0.12% – a figure quite close to the Column (1) results of Panel A. The wage consequences also diminish proportionally.

All of the columns in Panel A mirror those of Table 1, altering the assumed value of ρ and the underlying skill distribution. The largest difference in GDP gap estimates amounts to 0.06 percentage-points using an assumed value of $\rho = 0.36$. Potential gains from a change in policy range from \$8.3 to \$35.2 billion.

Panel B of Table 2 presents a final calibration exercise. This procedure recognizes that recent employment levels and factor income shares are quite different from values in 2000, with significant increases in the share of income paid to highly-educated workers and a decline in the share paid to less-educated labor. Like in Table 1, all highly-educated foreign-born workers are included in the construction of \hat{F} . Employment values and income shares are as recorded in the 2014 ACS. Namely, $\hat{F} = 6,695,098$ and $\{\lambda, \eta, \phi\} = \{0.47, 0.44, 0.09\}$. Again, the net effect of this alternative is small. Though the stock of educated foreign workers has grown (thus dampening the potential effect of a change in the annual flow of H-1B skills), the income share has grown too. Altogether, Table 1 and both panels of Table 2 combine to illustrate the robustness of estimates to different assumptions regarding parameter values and skill distributions.

5 Conclusion

H-1B policy limits the number of work permits for new, temporary, highly-educated, foreign-born employees of most firms to 65,000 per year, plus an additional 20,000 permits to workers who have obtained an advanced degree in the US. Educated labor is widely-recognized as a scarce and productive input into the production process. However, economists, policy-makers, and the popular press continue to debate the distributional effects of the H-1B program, such as implications for the employment opportunities of highly-educated native-born workers.

This paper takes no stance on the optimal number of permits that should be awarded, nor does it estimate the substitutability between college-educated native and foreign-born labor. Instead, it evaluates the method through which available permits are allocated. Strong H-1B demand has led USCIS to distribute permits according to a random lottery conducted among applications received in the first week of eligibility. An alternative method resulting in the same number of foreign workers could instead award permits to the highest-ability applicants as measured by wage offers reflecting workers' marginal product of labor.

This paper performs a calibration exercise to assess the differences between these two alternatives. It

begins by building a model with a simple production function incorporating low-education, high-education native-born, and high-education foreign-born labor. Workers of different types may be imperfectly substitutable with each other, but potential gains are restricted to the production process only. That is, the model does not allow gains associated with potential technological and productivity spillovers caused by the innovative capacity of highly-educated workers or immigrants more specifically.

Outcome differences associated with allocation policy alternatives can be ascertained from simulations that incorporate plausible parameter values and observed data from USCIS, Census, and ACS, as well as estimates from prior studies. The exercise uncovers at least six key insights about moving from an allocation method that distributes H-1B permits via random lottery to one that awards permits based upon ability.

First, the skill level of H-1B recipients could rise dramatically. Estimates suggest a 20-30% annual increase of foreign abilities, which implies a 2.5-4.5% increase in the stock of foreign skills over a six year period. Second, output and output per capita would unambiguously rise. Baseline estimates suggest a 0.15% over a six year period. This amount is approximately equal to \$26.5 billion in 2014.

Third, workers without a bachelor's degree would unambiguously benefit. However, individual wage gains are small and spread over a large number of people. Fourth, in the absence of technological spillovers, native-born workers with a bachelor's degree are likely to experience small wage losses. Baseline estimates suggest a wage loss of 0.10% over six years. The conditions that determine whether highly-educated native-born workers experience a wage increase in response to improved immigrant ability are the same conditions that determine whether an increase in the number of immigrants will have a positive wage effect.

Fifth, consequences of changing H-1B allocation policy are highly sensitive to the level of H-1B demand: As H-1B demand rises and scarcity becomes more acute, the output gap between allocation methods grows. H-1B demand for fiscal year 2017 implies that output would rise more than 0.20% by switching to an ability-based allocation system. Estimates are much less sensitive to other features of the model including assumed income shares, employment levels, and underlying H-1B skill distributions. Finally, the elasticity of substitution between educated native and foreign-born workers – a contested parameter estimate in the literature – plays no role in driving the average macroeconomic effects of the model. Instead, it affects the distribution of income between low and high education labor, with the former group being more likely to

benefit from ability-based permit allocation.

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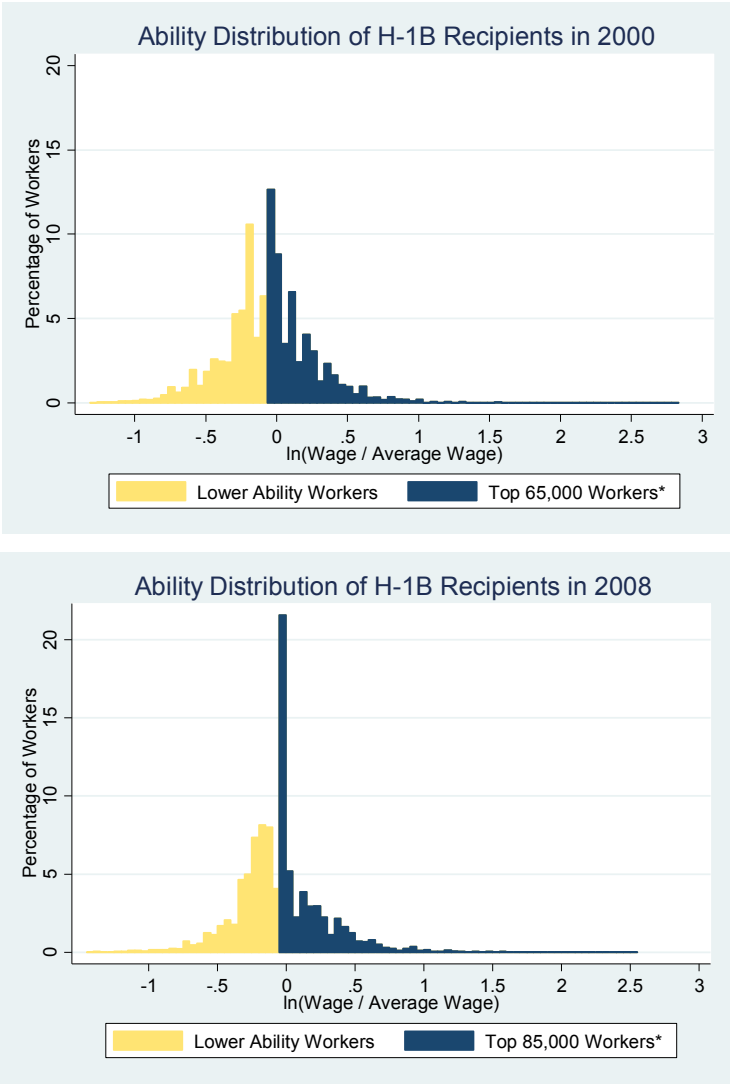
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6 Appendix

Output of the good produced by highly-educated workers (Y_H) is higher for Policy B than for Policy A if $\sum_{i=1}^{\rho \cdot F} q_i > \rho \cdot \sum_{i=1}^F q_i$. That is, $Y_B > Y_A$ if the total ability of the best $\rho \cdot F$ workers exceeds $\rho\%$ of the ability of all possible workers. Suppose that the function $f(F) = \sum_{i=1}^F q_i$ is strictly increasing, concave, and homogenous of degree $n \in (0, 1)$. Then the high-education output lost going from a level of $F = F_0$ to a level of output scaled by ρ is $(1 - \rho) \cdot f(F_0)$. This is the output lost under Policy B . Policy A instead scales F by a factor of ρ , resulting in lost high-education output equalling $f(F_0) - f(\rho \cdot F_0) = f(F_0) - \rho^n \cdot f(F_0) = (1 - \rho^n) \cdot f(F_0)$. Since both n and ρ are positive numbers less than one, we can see that lost output from Policy B is smaller. That is, Policy B results in more output, productivity, and wages paid to less-educated workers.

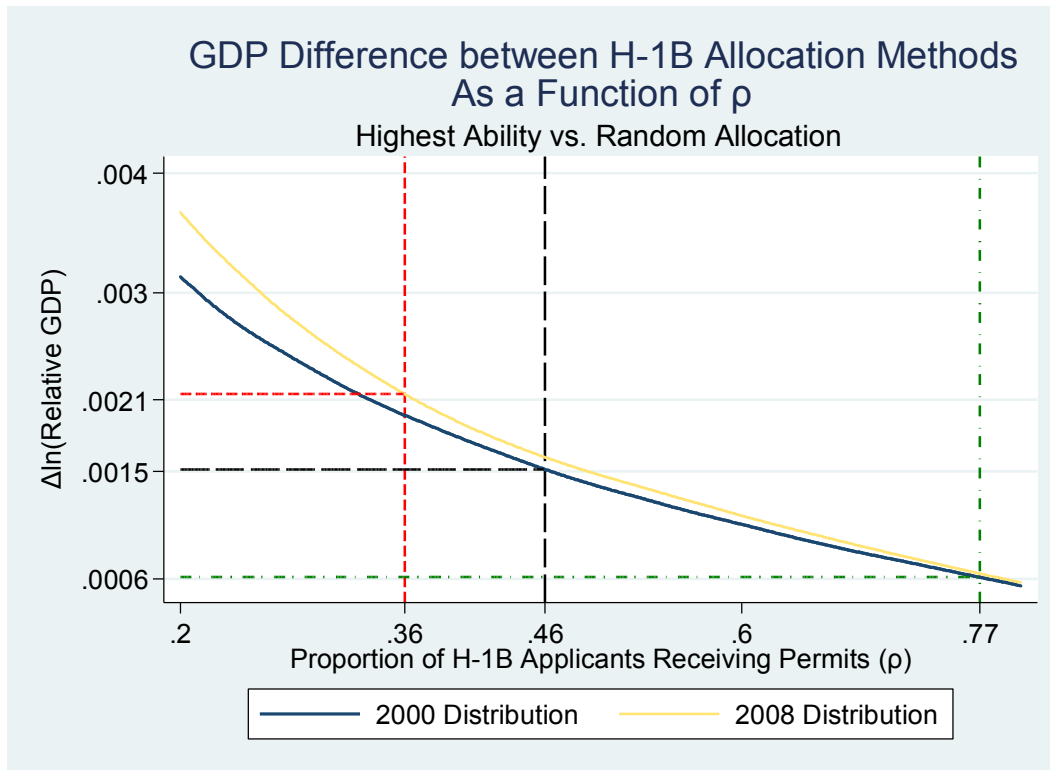
Graphical representation in Appendix Figure 1 helps to illustrate this effect. The total ability of high education foreign workers is identified by the curve Σq . In an unrestricted immigration regime in which F individuals migrate, the total ability is marked U . Policy A generates an expected skill level curve identified by $\rho \Sigma q$, with an overall expected skill, $E(Skill)$, identified by the value of this curve at F . The total number of workers admitted is equal to ρF . The expected outcome is marked A . Note, however, that Policy B would have selected the first ρF workers with the highest skill level. This corresponds to a total ability that falls along the original Σq curve marked B – a level exceeding the ability arising from Policy A . Ability-based work permit allocation leads to a higher level of skill supply than random allocation.

Figure 1: Ability Distribution (in Natural Logs) of 2000 and 2008 H-1B Recipients



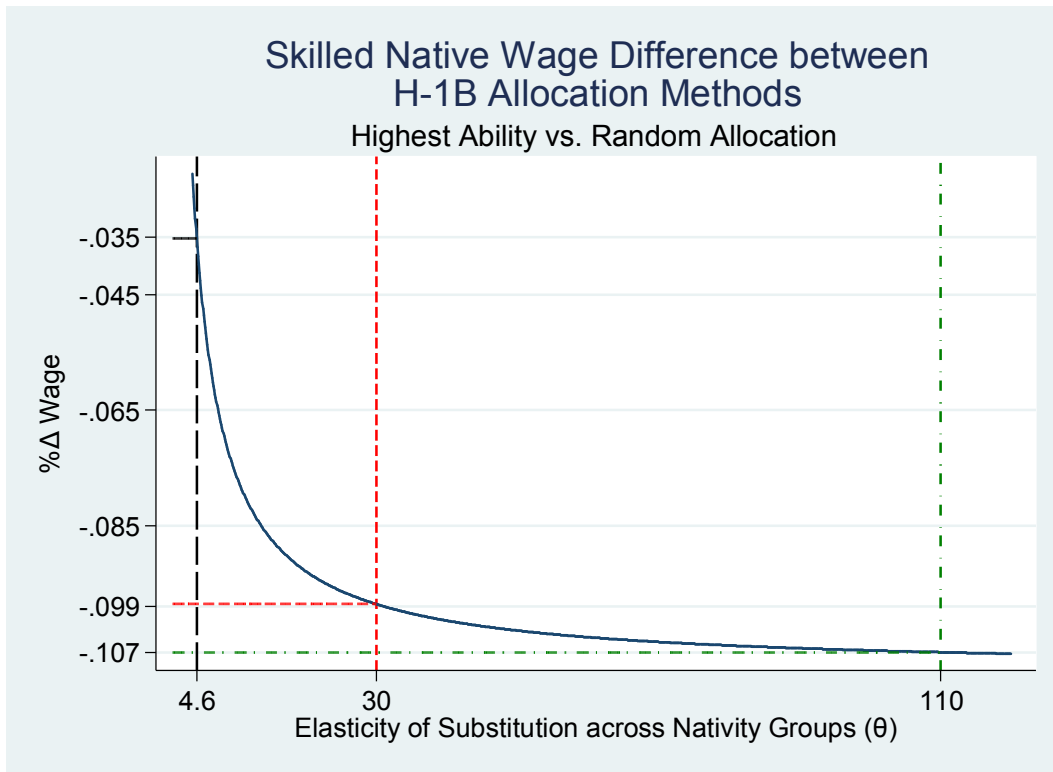
Ability (q) is measured by the wage offer paid to foreign workers, normalized by average wages. The distribution of q from H-1B applications received in the calendar year 2000 and from H-1B recipients during the first week of April 2008 (when available permits for fiscal year 2009 were exhausted) follow an approximate log-normal distribution with right skewness. If a cap of 65,000 permits had been implemented in 2000 with permits distributed to the highest ability workers, the log-ability distribution would have been represented by the blue shading in the top panel. If the pool of random winners is representative of the pool of interested applicants, then the blue shading in the bottom panel represents the log-ability distribution if 85,000 permits had been awarded based upon ability.

Figure 2: Comparing GDP from Lottery (A) and Ability-Based (B) Permit Allocation Policies as a Function of H-1B Demand



The figure represents the difference in GDP achievable under ability-based versus random allocation of H-1B permits, assuming the 2000 (thick blue line) or 2008 (yellow line) distribution of skills. With a fixed number of available work permits, an increase in H-1B demand reduces the proportion of applicants who receive permits (ρ). $\rho=0.46$ and $\rho=0.77$ represent hypothetical values if a 65,000 cap had been imposed in fiscal years 2001 and 2002, respectively. $\rho=0.36$ is the maximum value for fiscal year 2017 possible, based upon the 85,000 cap and the calculable portion of latent H-1B demand. Allocation that favors the highest-ability workers over random selection leads to particularly high skill contributions if more high ability workers are available. Thus, the gap in equivalent workers, and hence GDP, implied by the two policies grows as demand increases (falls as ρ approaches one).

Figure 3: Wages Paid to Skilled Native Workers; Comparison between Lottery and Ability-Based Permit Allocation Policies as a Function of Native and Foreign-Born Labor Substitutability



The elasticity of substitution between native and foreign-born college-educated workers (θ) only has distributional consequences on the effects of switching from random to highest-ability H-1B allocation. Wages paid to highly-educated native-born workers are more likely to decline as they are more substitutable with H-1B workers. Model parameters are calibrated to match observed employment levels and income shares in 2000. Estimated elasticities from the literature typically cluster around $\theta=30$ (the value assumed in most of this paper), with figures ranging from $\theta=4.6$ to $\theta=110$ (or higher).

Table 1: Simulated Effects of Moving from a Lottery to an Ability-Based H-1B Permit Allocation Method

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Success Proportion (ρ) Year	2000	2001	2016	2000	2001	2016	2016
Skill Distribution Year	2000	2000	2000	2008	2008	2008	2008*
	<u>Assumed Values</u>						
Assumed Quota	65000	65000	85000	65000	65000	85000	79864
Highest Skill Alternative	82270	71940	114470	81126	71385	113074	106225
ρ	0.46	0.77	0.36	0.46	0.77	0.36	0.36
	<u>Simulated Values</u>						
%Δ Foreign Skill, Single Year	23.56%	10.14%	29.77%	22.16%	9.37%	28.54%	28.52%
%Δ Foreign Skill, Total	2.89%	1.17%	4.88%	2.70%	1.08%	4.65%	4.37%
%Δ GDP	0.15%	0.06%	0.26%	0.14%	0.06%	0.24%	0.23%
%Δ Wage, Less-Educated	0.09%	0.04%	0.15%	0.08%	0.03%	.014%	0.13%
%Δ Wage, High-Educated Natives	-0.10%	-0.04%	-0.17%	-0.09%	-0.04%	-0.16%	-0.15%
GDP Gain (\$Billions, 2014)	26.49	10.74	44.76	24.76	9.88	42.69	40.48

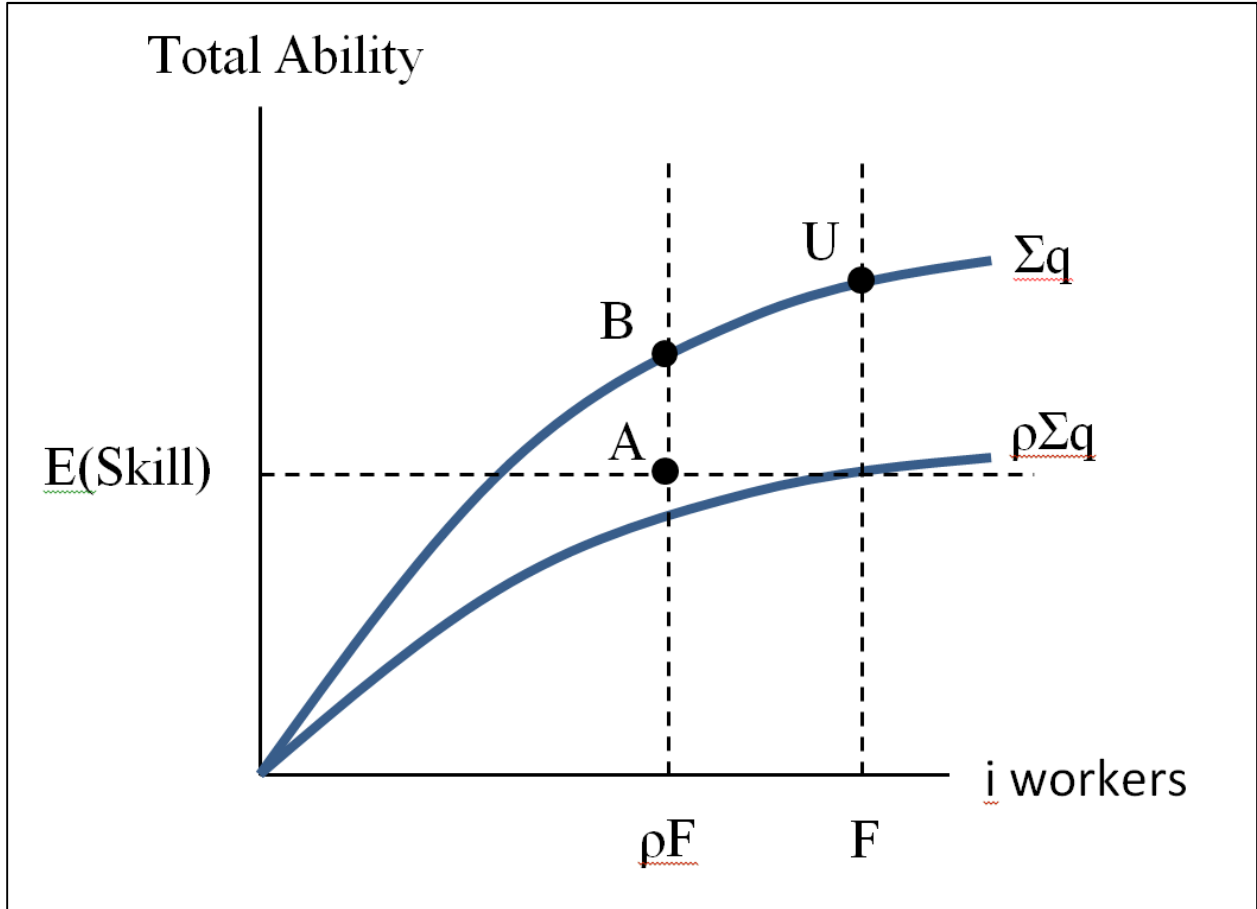
Table reports simulated effects of moving from a lottery to an ability-based H-1B permit allocation method on the supply of foreign skills (F_B/F_A), output (Y), wages paid to workers without a bachelor's degree (W_L), and native-born workers with a bachelor's degree or more education (W_N). The final row presents the implied gain in GDP given real GDP in 2014 equal to \$17.46 trillion. The table uses 2000 Census data to set income shares of less-educated, highly-educated native, and highly-educated foreign workers equal to 0.56, 0.39, and 0.05 respectively. Columns are differentiated by different assumptions regarding the probability of winning a work permit and the underlying skill distribution. * Indicates that the final column normalizes 2008 skills so that they are centered at the 2000 wage distribution.

Table 2: Simulated Effects of Moving from a Lottery to an Ability-Based H-1B Permit Allocation Method, Alternative Construction of Foreign-Born Labor Force

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Success Proportion (ρ) Year	2000	2001	2016	2000	2001	2016	2016
Skill Distribution Year	2000	2000	2000	2008	2008	2008	2008*
	<i>Assumed Values</i>						
Assumed Quota	65000	65000	85000	65000	65000	85000	79864
Highest Skill Alternative	82270	71940	114470	81126	71385	113074	106225
ρ	0.46	0.77	0.36	0.46	0.77	0.36	0.36
	<i>Panel A: Simulated Values; $\{\lambda, \eta, \phi\}=\{0.56, 0.43, 0.01\}$</i>						
% Δ Foreign Skill, Single Year	23.56%	10.14%	29.77%	22.16%	9.37%	28.54%	28.52%
% Δ Foreign Skill, Total	12.63%	5.27%	20.68%	11.84%	4.86%	19.79%	18.69%
% Δ GDP	0.12%	0.05%	0.20%	0.12%	0.05%	0.19%	0.18%
% Δ Wage, Less-Educated	0.07%	0.03%	0.12%	0.07%	0.03%	0.11%	0.10%
% Δ Wage, High-Educated Natives	-0.08%	-0.03%	-0.13%	-0.08%	-0.03%	-0.13%	-0.12%
GDP Gain (\$Billions, 2014)	21.51	8.97	35.22	20.17	8.27	33.71	31.83
	<i>Panel B: Simulated Values; $\{\lambda, \eta, \phi\}=\{0.47, 0.44, 0.09\}$</i>						
% Δ Foreign Skill, Single Year	23.56%	10.14%	29.77%	22.16%	9.37%	28.54%	28.52%
% Δ Foreign Skill, Total	1.54%	0.62%	2.61%	1.43%	0.57%	2.48%	2.33%
% Δ GDP	0.13%	0.05%	0.23%	0.12%	0.05%	0.21%	0.20%
% Δ Wage, Less-Educated	0.08%	0.03%	0.13%	0.07%	0.03%	0.12%	0.12%
% Δ Wage, High-Educated Natives	-0.06%	-0.02%	-0.10%	-0.06%	-0.02%	-0.10%	-0.09%
GDP Gain (\$Billions, 2014)	23.19	9.36	39.35	21.66	8.61	37.51	35.25

Table reports simulated effects of moving from a lottery to an ability-based H-1B permit allocation method on the supply of foreign skills (F_B/F_A), output (Y), wages paid to workers without a bachelor's degree (W_L), and native-born workers with a bachelor's degree or more education (W_N). The final row presents the implied gain in GDP given real GDP in 2014 equal to \$17.46 trillion. Panel A uses 2000 Census data to set income shares and assumes that established immigrants in the US for more than six years are perfectly substitutable with natives. Panel B uses 2014 ACS data for income shares and assumes all highly-educated foreign workers are grouped together. Columns are differentiated by different assumptions regarding the probability of winning a work permit and the underlying skill distribution. * Indicates that the final column normalizes 2008 skills so that they are centered at the 2000 wage distribution.

Appendix Figure 1: Theoretical Skill Comparison between Lottery (A) and Ability-Based (B) Permit Allocation



Individual workers (i) are ordered from highest to lowest ability. Σq represents the total ability of workers, which reaches a level marked by U at a total of F workers. If policy allows only a fraction (ρ) of randomly-selected workers to enter the country, the expected ability is $\rho \Sigma q$. The number of workers and expected ability is marked by A . If the workers selected for entry are instead the ρF workers of highest ability, the outcome is marked by point B .

Appendix Table 1: Summary Statistics for ln(Wage) in 2000 and 2008 for H-1B Recipients or Census/ACS Workers

	2000					2008				
	Mean	SD	25th	Median	75th	Mean	SD	25th	Median	75th
H-1B	10.910	0.371	10.714	10.897	11.156	11.078	0.385	10.835	11.002	11.314
Cap-Bound	10.826	0.325	10.645	10.820	11.002	10.995	0.315	10.820	11.002	11.106
Cap-Exempt	10.975	0.390	10.714	11.002	11.225	11.103	0.401	10.840	11.051	11.356
Foreign College-Educated (Census/ACS)	10.810	0.950	10.366	10.889	11.381	10.843	0.957	10.358	10.943	11.418
Native College-Educated (Census/ACS)	10.807	0.927	10.443	10.884	11.321	10.825	0.955	10.444	10.907	11.360
Non-College Educated (Census/ACS)	10.177	0.886	9.786	10.321	10.730	10.163	0.923	9.751	10.319	10.746
Subsets of Cap-Bound Foreign College-Educated										
India	10.830	0.215	10.714	10.820	10.933	10.987	0.220	10.859	11.002	11.051
China	10.897	0.315	10.714	10.915	11.097	11.093	0.362	10.859	11.127	11.356
Philippines	10.627	0.362	10.370	10.609	10.859	10.849	0.367	10.645	10.859	11.002
United Kingdom	11.107	0.507	10.758	11.128	11.424	11.301	0.560	10.915	11.329	11.695
South Korea	10.767	0.438	10.428	10.714	11.115	10.835	0.457	10.519	10.779	11.156
Computer-Related	10.851	0.229	10.714	10.820	10.968	10.987	0.212	10.859	11.002	11.044
Engineering & Architecture	10.882	0.345	10.645	10.897	11.097	11.093	0.301	10.907	11.082	11.290
Managers	10.707	0.485	10.348	10.597	11.002	10.934	0.447	10.632	10.867	11.184
Bachelors	10.779	0.301	10.639	10.779	10.915	10.947	0.277	10.820	10.985	11.029
Masters	10.871	0.305	10.714	10.851	11.035	10.998	0.296	10.820	11.002	11.142
Professional	11.178	0.570	10.714	11.302	11.665	11.608	0.629	11.142	11.775	12.044
Doctorate	11.123	0.345	10.931	11.156	11.321	11.305	0.306	11.156	11.339	11.465

Table reports the mean, standard deviation (SD), 25th percentile, median, and 75th percentile of ln(wage) in 2000 and 2008. Figures are based upon H-1B recipients unless Census/ACS notes otherwise.