Online Appendix for: "How Does Labor Mobility Affect Corporate Leverage and Investment?"

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Abstract

This appendix contains supplementary material to the analysis in the paper. Section 1 provides details on the numerical solution of the model and the estimation of the model parameters using the Simulated Method of Moments (SMM). Section 2 presents tests of the impact of labor mobility on firm policies using alternative measures of leverage and cash holdings. Section 3 presents cross-sectional evidence on the link between mobility and firm's decisions using an alternative measure of mobility developed by Donangelo (2014).

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1 Structural Estimation of the Model

This section provides details on the structural estimation of the model parameters. In what follows, I first discuss the process of solving the model numerically, which results in the firm's value and policies as a function of model parameters. Next, I discuss the mechanics of estimating the model parameters through indirect inference by matching the model to the data. Finally, I review the choice of moments and parameter identification.

1.1 Model Solution

The model is solved numerically via value function iteration using the Bellman equation described in Equation (7) in the main paper. To make the numerical solution and estimation process computationally feasible, I reduce the firm's state space by defining $E(Z, K, L, B)$ as a new state variable that summarizes the impact of $\{K, L, B\}$ on dividends D. The goal is to write the firm's value function in the form of $V(Z, X, E)$. The variable $E(.)$ can be interpreted as the liquid internal funds before wage payments and new investment.

To this end, dividend D must be an additively separable function of current capital, labor, and debt $\{K, L, B\}$, and firm policies $\{K', L', B'\}$. According to Equation (5) in the main paper, this is possible only if both capital and labor adjustment cost functions are additively separable in current- and next-period values of capital and labor. Standard quadratic adjustment cost functions (e.g., Hayashi, 1982) do not have this property. I adopt modified quadratic cost functions to be relatively close to the standard form and also to be able to reduce the state space dimension. The adjustment cost functions are

$$\phi_K(K', K) = \frac{c_k}{2}K - c_k K' + \frac{c_k}{2}\frac{K'^2}{K^*} = \phi_K^1(K) + \phi_K^2(K') \tag{1}$$

$$\phi_L(L', L) = \frac{c_l}{2}L - c_l L' + \frac{c_l}{2}\frac{L'^2}{L^*} = \phi_L^1(L) + \phi_L^2(L') \tag{2}$$

where $\phi_K^1(K) = \frac{c_k}{2}K$, and $\phi_K^2(K') = -c_k K' + \frac{c_k}{2}\frac{K'^2}{K^*}$; their labor counterparts are defined similarly. The terms K^* and L^* are the steady state values of capital and labor when the firm's productivity is constant at Z. Note that a standard quadratic capital adjustment cost is $\frac{c_k}{2}K(\frac{K'-K}{K})^2 = \frac{c_k}{2}K - c_k K' + \frac{c_k}{2}\frac{K'^2}{K}$. I modify this by replacing K with K^* in the last term.

In practice, the difference between the standard form and my cost functions is relatively small in the model simulations.

Substituting Equations 1 and 2 in Equation (5) in the main paper, I can define $E(.)$ as

$$E(Z, K, L, B) = (1 - \tau_c)Y + \tau_c \delta_k K + (1 - \delta_k)K - B - \phi^1_K(K) - \phi^1_L(L), \tag{3}$$

and dividend D can be rewritten as

$$D(Z, X, E, K', L', B') = E - (1 - \tau_c)W'L' - K' + \frac{B'}{1 + (1 - \tau_c)r'} - \phi^2_K(K') - \phi^2_L(L'). \tag{4}$$

Hence, the Bellman equation representing the firm's problem becomes

$$\begin{aligned} V(Z, X, E) = &\max \left\{0, \max_{K',L',B'} \left\{D + \eta(D) + \beta \mathbb{E}\left[V(Z', X', E')\right]\right\}\right\} \\ \text{subject to} \quad &\text{Equation 4, and Equations 3, 4, 6, 18 from the main paper.} \end{aligned} \tag{5}$$

To perform value function iteration on the above Bellman equation, I discretize the state and policy spaces. The AR(1) process for the idiosyncratic productivity is discretized on a grid with $N_Z = 9$ points, and the transition matrix is computed using the algorithm in Tauchen and Hussey (1991).

The outside offer X, defined in Equation (12) in the main paper, is an *i.i.d.* stochastic process and has an equally spaced grid with $N_X = 9$ points over the range $[X_0, \bar{X}]$. The lower bound X_0, which is the reservation value if there is no outside job offer, is set equal to the skill level s.[1] We want the range of X to be large enough to reflect the potential extreme-value job offers, but not too large so that it could be reasonably covered by the grid points. I find by trial and error that setting the upper bound $\bar{X}$ equal to 3 serves both purposes fairly well.

The probability vector for the X grid points, Π_X, is computed according to both the mobility parameter and the fact that outside offers have an exponential distribution with the parameter $\frac{1}{s}$. First, I ignore mobility and compute a generic probability vector Π for a

[1]This implies that high-skill workers (higher s) drive higher value from unemployment. This could be justified by high-skill workers' ability to freelance. As discussed below, s takes the value of 0.33 and 1 for low- and high-skill workers, respectively.

grid of 9 equally spaced points spanning from 0 to 5 (this is an arbitrarily large number, but not too large), using the exponential distribution CDF, $1 - \exp(-\frac{1}{s}x_i)$, where $x_i = 0, \frac{5}{8}, ..., 5$. Next, I assign $1 - m$ to the first element of Π_X and set its second to ninth elements equal to the corresponding elements of Π multiplied by m.

Figure 1 in the main paper illustrates the impact of mobility and skill on the probability distribution over the X grid points. Figure 1a shows that for a constant skill level, as mobility increases, the probability of no outside offer X_0, the first element on the X grid, decreases, and the probability of receiving an outside job offer, second to ninth elements, increases. Figure 1b shows that at a constant mobility level, as skill increases, the distribution of job offers, second to ninth points on the X grid, becomes flatter: lower-value job offers (e.g., the second grid point) have lower probability, and higher-value job offers (e.g., the third to ninth grid points) have higher probability. This increases the expected value of job offers and implies that high-skill workers, all else equal, have a better chance of receiving high-value outside offers.

The capital grid, following Hennessy and Whited (2007), is geometrically spaced using $(1 - \delta_k)^{n_k}$ as the multiplicative factor, and with $N_K = 75$ grid points:

$$[\bar{K}(1 - \delta_k)^{n_k \times N_K}, \bar{K}(1 - \delta_k)^{n_k \times (N_K - 1)}, ..., \bar{K}(1 - \delta_k)^{n_k}], \tag{6}$$

where n_k is set such that the smallest point on the grid is 0.01 of the largest point on the grid, and $\bar{K}$ equals 20% of the steady state level of capital when productivity is constant at the highest level of the Z grid. These choices ensure that the first grid point is small enough and the last grid point is large enough that these bounds are never binding.

Similarly, the labor grid is geometrically spaced using $(1 - \delta_l)^{n_l}$ as the multiplicative factor, and with $N_L = 75$ grid points. Also, n_l and $\bar{L}$ are set in the same way as their capital counterparts.

The debt grid points are symmetric around zero and geometrically spaced on each side with total $N_B = 45$ grid points. As mentioned before, B is net corporate debt, with positive values interpreted as borrowing and negative values interpreted as savings. On the positive side of the grid, the lower bound has half the value of the lower bound of the capital grid, and the upper bound is equal to the upper bound of the capital grid. Debt grid points below zero are negative of the positive grid points.

Finally, I create the E grid with $N_E = 100$ points. Computing all possible values of E using the grid points of Z, K,L, and B in Equation 3 produces a fine grid for E with $N_Z \times N_K \times N_L \times N_B$ points. I sort these points and create a coarse grid for E with N_E points, preserving the density of the original finer grid. Using the coarse grid for E along with interpolations speeds up the numerical part significantly and makes the model estimation feasible.

The numerical solution proceeds in two steps, following Hennessy and Whited (2007). First, I start with an initial guess for the interest rate schedule, $r'(Z, X, K', L', B') = r_f$, and solve for the value function in Equation 5. Second, the solution for the value function is used to identify default states, and the interest rate structure is updated according to Equation (8) in the main paper. I then iterate on this two-step procedure until both the value function and the interest rates converge.

1.2 Simulated Method of Moments

I estimate most of the model parameters using SMM. However, to reduce the computational burden, some parameters are estimated directly from data or other studies.

Predefined Parameters. The annual risk-free rate r_f is estimated at 4.6%, which is the average rate on 3-month Treasury bills over the estimation sample period, 1960 to 2019. I set the corporate tax rate τ_c at 30% and the personal (investors') tax rate τ_p at 25%, in line with the US tax rates estimated by Graham (2000). The discount rate for equity investors is then computed as $\beta = \frac{1}{1+(1-\tau_p)r_f}$, accounting for taxes paid on the interest from alternative investment opportunities (e.g., risk-free bonds). Workers discount future utility with $\beta_L = \frac{1}{1+r_f}$.

The natural separation rate for labor δ_L is set to 3.5%, using the estimation by the Job Openings and Labor Turnover Survey for annual rate of separations from retirement, death, disability, etc. I set the equity issuance cost parameters according to a linear estimation by Gomes (2001). So, the fixed flotation cost η_1 is set to the model equivalent of $0.48 million, and the linear cost is $\eta_2 = 2.8\%$.[2]

Finally, I set the skill parameter s for high-skill firms to 1 and for low-skill firms to 0.33, following Belo, Lin, Li, and Zhao (forthcoming). They back out this relative measure of skill from wages paid to high-skill and low-skill workers.

Estimation Procedure. The remaining structural parameters are estimated through SMM, which I adapt to my panel setting following Nikolov and Whited (2014). Let $\hat{\boldsymbol{M}}$ be a vector of moments estimated from the data, and $\hat{\boldsymbol{m}}^s(\Theta)$ be the corresponding vector of moments estimated from the s^{th} sample simulated using parameters $\Theta = \{\alpha, \nu, \rho, \sigma, \delta_k, c_k, c_l, \xi, m, \theta\}$, where $s = 1, ..., S$. The SMM estimator $\hat{\Theta}$ is

$$\hat{\Theta} = \underset{\Theta}{\operatorname{argmin}} \left(\hat{\boldsymbol{M}} - \frac{1}{S} \sum_{s=1}^{S} \hat{\boldsymbol{m}}^s(\Theta) \right)' \hat{W} \left(\hat{\boldsymbol{M}} - \frac{1}{S} \sum_{s=1}^{S} \hat{\boldsymbol{m}}^s(\Theta) \right), \tag{7}$$

where $\hat{W}$ is a positive definite weighting matrix, which is equal to the inverse of a covariance matrix that is calculated using the influence function approach in Erickson and Whited (2002). In particular, I create a vector of the influence functions of the moments for all observations and take the sample average of the inner product of these vectors. I use the simulated annealing algorithm to find the global solution to the above optimization problem.

To compute the model-generated moments, I use policy functions to create S simulated panels of size $(N, T + 50)$, where N is the number of firms in the actual data, and T is the average number of years a firm exists in the actual data. I use $S = 20$ simulated samples to be conservative.[3] Then the first 50 years of the panel are discarded, allowing the final simulated sample to have a stationary distribution, after firms work their way out of the starting point.

The actual data are from CRSP-Compustat merged dataset and cover the period from 1960 to 2019. In addition to the filters that I use on the data in the empirical section of the main paper, I only keep firms with more than three consecutive years in the dataset. This additional step makes the computation of standard deviation and autocorrelation moments

[2] In the model, η_1 is computed by multiplying the midpoint value of the capital grid by 0.0003, which is the fixed flotation cost in the data ($0.48 million) as a fraction of the median of total assets in my sample.

[3] Michaelides and Ng (2000) show that a simulated sample 10 times as large as the empirical sample has acceptable finite sample properties.

more precise.

Another issue is to account for the fact that the actual data consist of a panel of firms with unobservable heterogeneity, but the simulated data consist of ex ante identical firms. To make these two samples comparable, I take out the heterogeneity in the actual data. I transform the actual data by demeaning each variable at the firm level and adding back the grand mean of the panel. So, the standard deviations only capture the within firm variation while the means are preserved. Note that I use the transformed data in calculating both the actual moments and the weight matrix. The only exception is the autocorrelation moments and their corresponding elements in the weight matrix. To get a consistent estimation of autocorrelations, I use the raw (untransformed) data in the first difference method of Han and Phillips (2010). Then the estimated autocorrelation coefficients along with the raw data are used to compute the influence functions of these moments for the weight matrix.

Note that I calculate standard errors of the parameters using the clustered moment covariance matrix, which accounts for temporal dependence in the data.[4]

1.3 Choice of Moments and Identification

Reliability of the estimation results critically depends on choosing the moments that are sensitive to variations in the structural parameters. Although all of the parameters affect all of the moments in some way, some moments have stronger monotonic ties to particular parameters because of the model structure. I start with an intuitive discussion of the links between the parameters and selected moments. This is followed by a more formal test of parameter identification with respect to moments.

Moments. Some of the links between parameters and moments are more straightforward and discussed extensively in the literature. For instance, technology parameters are most directly related to moments of investment, wage bill, and income. Specifically, α positively affects the firm's sensitivity of investment to productivity shocks, so it is positively related to the standard deviation of investment. Also, α is negatively related to the mean of

[4]Although $\hat{W}$ used in Equation 7 reflects within-firm variations that are useful for the estimation process, it is not the optimal weight matrix because it does not account for any temporal dependence in the data. See Nikolov and Whited (2014) for more details on the calculation of the clustered moment covariance matrix and the covariance matrix for the parameters.

income to assets because as α increases, firms increase capital stock relative to the flow of income. The parameter ν is positively related to the labor share, so the mean of wage bill to income is increasing in this parameter. Also, ν positively affects the sensitivity of hiring to productivity shocks, so it is positively related to the standard deviation of employment growth.

The capital depreciation rate δ_k is strongly identified by the mean of investment rate. The productivity parameters ρ and σ are also directly related to serial correlation and standard deviation of income. The adjustment costs in general dampen factor adjustments in response to firms' productivity. Therefore, c_k and c_l are negatively related to the standard deviations of investment rate and employment growth, respectively. Also, to the extent that firms use external funds to finance investment and employment, these two parameters are negatively related to the standard deviation of leverage.

Next, I select moments that are sensitive to the labor bargaining power θ and labor mobility m. The parameter θ determines the share of total surplus that goes to workers, so it is positively linked to the mean of wages to income and wages to assets. Michaels, Page, and Whited (2016) suggest using moments of firms' dividends because a higher θ generally leaves fewer resources in the firm, thus decreasing the mean and the standard deviation of distributions per unit of capital. Moreover, θ is positively related to both the mean and standard deviation of leverage. Finally, labor mobility m, by increasing the frequency of outside offers, is positively related to the standard deviation of wages, and to the mean of leverage and investment, as discussed in model descriptions in the main paper. Also, the standard deviation of leverage is increasing in m and the autocorrelation of leverage is decreasing in m.

Identification. I also show more formally how the model parameters are identified in practice, by computing the local elasticity of moments with respect to estimators, following Hennessy and Whited (2007). The intuition is that a particular parameter is precisely estimated if at least one moment is adequately sensitive to it, since moving away from the true parameter value makes the simulated moment very different from the target data moment. Results are generally consistent with the intuitive discussion of moments' selection.

I compute the elasticity of moments with respect to model parameters around the SMM estimates for high-skill firms.[5] I compute the elasticities as follows. Suppose we want the elasticity of the ith moment $\hat{\boldsymbol{m}}_i(\hat{\Theta})$, with respect to the jth parameter Θ_j. Having all other parameters fixed at their SMM estimates, I simulate the model with different values of $\Theta_j \in [0.90\hat{\Theta}_j, 1.10\hat{\Theta}_j]$ (with 1% increments) and compute $\hat{\boldsymbol{m}}_i(\Theta_j; \hat{\Theta})$ respectively, where $\hat{\Theta}_j$ is the SMM estimate of the jth parameter. The elasticity is then

$$\epsilon_{i,j} = \frac{\hat{\boldsymbol{m}}_i^+(\Theta_j; \hat{\Theta}) - \hat{\boldsymbol{m}}_i^-(\Theta_j; \hat{\Theta})}{\Theta_j^+ - \Theta_j^-} \times \frac{\hat{\Theta}_j}{\hat{\boldsymbol{m}}_i(\hat{\Theta})}, \tag{8}$$

where Θ_j^- and Θ_j^+ are the average values over $[0.90\hat{\Theta}_j, \hat{\Theta}_j]$ and $[\hat{\Theta}_j, 1.10\hat{\Theta}_j]$, respectively. The values $\hat{\boldsymbol{m}}_i^-(\Theta_j; \hat{\Theta})$ and $\hat{\boldsymbol{m}}_i^+(\Theta_j; \hat{\Theta})$ are the averages of the ith moment over the respective range of Θ_j, and $\hat{\boldsymbol{m}}_i(\hat{\Theta})$ is the simulated value of the ith moment at the SMM solution.

Table 1 presents the estimated elasticities. For easier readability, only elasticities with absolute values greater than 0.5 are shown. Numbers in the table measure the percentage change in each moment as a result of a 1% increase in a single parameter, ceteris paribus. Note that these elasticities are locally estimated around the SMM solution, and the empty cells in Table 1 do not necessarily imply the lack of identification power between particular moments and parameters. It is possible that a moment has a small local sensitivity to a parameter but helps to identify that parameter over a wider range.

Results are generally consistent with the intuitive discussion of the moments' selection. For instance, the second to last column of Table 1 shows the elasticities with respect to mobility m. The most sensitive moments to m are the standard deviation and autocorrelation of leverage and the standard deviation of wages. A 1% increase in mobility m raises the volatility of wage bill to assets (income) by 0.55% (0.92%). It also increases the volatility of leverage by 0.68% and decreases the autocorrelation of leverage by 0.76%. These effects are consistent with the model mechanism in which a higher mobility makes the outside job offers more volatile, leading to a more volatile leverage policy by the firm.

The last column of Table 1 shows the impact of a 1% increase in bargaining power θ on moments. The volatility of wage bill to income and the volatility of employment growth are

[5] For the sake of brevity, I only present the elasticity table for the estimation of high-skill firms; however, results are qualitatively consistent across both groups.

among the most sensitive moments to θ and are decreased by 0.68% and 0.59%, respectively. The mean of distributions is also negatively affected by 0.77%, confirming the negative relation between payouts to shareholders and the labor share of surplus. Finally, the mean and standard deviation of leverage are positively affected by 0.60% and 0.73%, respectively, while the autocorrelation of leverage is decreased by 0.62%. These effects show that in response to an increase in θ, the firm has an incentive to increase leverage on average and use it as a bargaining tool more frequently. This is consistent with the strategic use of leverage, which is a pillar for the model mechanism to rationalize the empirical findings.

2 Tests of Labor Mobility with Alternative Measures of Leverage and Cash Holding

Table 2 shows the results of IV regressions with alternative definitions of leverage and cash holding. The set of controls in the leverage regressions are the same as in the baseline regressions in the main paper. In the cash holding regressions, I control for market leverage, investment rate, and R&D expenditure as additional firm characteristics following Bates, Kahle, and Stulz (2009).

Columns 1 and 2 of Table 2 show the estimates from the first and second stages, respectively, of the IV regressions when the dependent variable is net book leverage (instead of net market leverage in the main paper). Results are qualitatively similar to the baseline case, that is labor mobility negatively impacts firms' leverage, but the link is only statistically significant for high skill firms.

Another robustness check is to distinguish the impact of mobility on leverage and cash. In the baseline tests, leverage is measured as net market leverage, which is measured as total debt minus cash over the firm's market value. Columns 3-6 of Table 2 show the impact of labor mobility separately on pure debt leverage, defined as total debt over firm's market value, and on cash holdings, measured as the ratio of cash and cash equivalents to assets. Columns 3 and 4 show the estimates from the first and second stages of the IV regression where the dependent variable is pure debt leverage. Column 4 results suggest that the pure debt leverage of high skill firms is negatively affected by labor mobility, but there is no effect on low skill firms. This is qualitatively similar to the findings in the baseline case.

Columns 5 and 6 of Table 2 show the estimates from the first and second stages of the cash holding regressions. The positive coefficient on the interaction of labor mobility and the high-skill indicator suggests that an increase in labor mobility increases cash holdings in high-skill firms, but there is no effect on low-skill firms. This is consistent with the idea that high-skill firms seek to increase their financial flexibility in response to higher labor mobility. However, the economic magnitude of the impact on cash holdings is much smaller that the leverage effects, suggesting that firms mainly adjust their debt policy in response to changes in labor mobility.

3 An Alternative Measure of Labor Mobility

I further study the links between labor mobility and firm decisions using an alternative measure of labor mobility developed by Donangelo (2014). The goal is to ensure that the main findings are not a particular feature of the mobility measure that I construct in the paper. Below I detail the construction of Donangelo's measure and investigate the connection between mobility, skill and firm policies using panel and cross-sectional regressions. All of the results are consistent with my baseline findings.

3.1 Constructing the Measure

I follow Donangelo (2014) to create an alternative mobility measure. This measure is created based on industry-level data on occupational employment. Due to the lack of firm-level employment by occupation data, this measure is also not available at the firm-level for all firms. However, following his methodology and using the detailed data on airlines from the US Department of Transportation, I create this mobility measure at the firm-level for airlines.

The process of constructing this measure is as follows. I get the employment and wage data for all occupations in each industry from 1999 to 2019, from Bureau of Labor Statistics (BLS), Occupational Employment Program. The data is available by 3-digit SIC until 2001, and by 4-digit NAICS from 2002 onward. To reduce the concerns about changes in the standards and definitions of occupations by the BLS, I limit the sample to only after the last change in occupation definitions in 1999. The other benefit of using this sub-sample is that the employment and wage data are based on annual surveys.[6]

First, I calculate a measure of concentration for each occupation,

$$conc_{j,t} = \sum_i \big(\frac{emp_{i,j,t}}{\sum_i emp_{i,j,t}}\big)^2 \tag{9}$$

where $emp_{i,j,t}$ shows the number of workers employed in industry i, in occupation j, at year t. If an occupation exists in many industries, it has a low concentration, and vice versa. For instance, medical doctors have high concentration (only in a few industries) while sales managers have low concentration (in many industries). Table 3, Panel A, shows occupations with highest and lowest concentrations in different skill groups.

Labor mobility at each industry is computed as the inverse of the weighted average of concentrations across all jobs in that industry:

$$Mobility_{i,t} = \Big(\sum_j \big[conc_{j,t} \times \frac{emp_{i,j,t} \times wage_{i,j,t}}{\sum_j (emp_{i,j,t} \times wage_{i,j,t})}\big]\Big)^{-1} \tag{10}$$

where $wage_{i,j,t}$ is the wage in industry i, for occupation j, at year t. The weighting of jobs within each industry is based on total wage bill of each occupation, i.e. $emp_{i,j,t} \times wage_{i,j,t}$. So, an industry that employs a lot of medical doctors (or other high concentration jobs) has low labor mobility, and an industry who employs a lot of sales managers (or other low concentration jobs) has high labor mobility.

Table 3, Panel B, shows industries with lowest and highest mobility measures in different skill groups. High skill industries are the top half of the sort on the average skill measure, and vice versa. Figure 1 plots mobility and skill measures for select industries over the sample period. While there is some variation in the measures within industries, most of the variation comes from between them.

To calculate these measures at the firm-level for airlines, I use Air Carrier Financial Re-

[6]Before 1997, the survey for occupations was done every three years.

ports from Bureau of Transportation Statistics of the US Department of Transportation. I use Form 41, schedule P-10 to get the annual employment statistics by labor category (occupations). Then I match these occupations with their Standard Occupational Classification code in the Dictionary of Occupational Titles and find average wage, skill and mobility similar to above (i indexes each airline, instead of industry). The balance sheet and profit and loss statement data for airlines are from Form 41, schedule B-1 and schedule P-1.2 (for large certified U.S. carriers with annual operating revenues of $20 million or more), and schedule B-1.1 and schedule P-1.1 (for U.S. air carriers with annual operating revenues of less than $20 million). The airline data spans from 1990 to 2019, however I am constrained by the occupations data so the final airline data set in my analysis is from 1999 to 2019. Due to the small sample, airline tests will be complementary to the more general tests using all US firms with the industry-level measures.

3.2 Regression Results

In addition to the alternative mobility measure, I use the skill measure explained in the paper to conduct the following tests.

Capital Structure. I start by examining the effect of labor skill and mobility on firms' capital structure. I regress financial leverage on the interaction of skill and mobility, controlling for observable firm characteristics. Equation 11 outlines the specification:

$$\begin{aligned} Lev_{fit} =& \alpha_f + \gamma_t + \beta_1 Skill_{it} * Mobility_{it} + \beta_2 Skill_{it} + \beta_3 Mobility_{it} + \beta_7 Q_{fit-1} \\ &+ \beta_6 Profit_{fit-1} + \beta_4 Size_{fit-1} + \beta_5 Tang_{fit-1} + \beta_8 IndLev_{it-1} + \varepsilon_{fit} \end{aligned} \tag{11}$$

where f indexes firm, i indexes industry and t is the year subscript. Q_{fit} is Tobin's Q, $Profit_{fit}$ is operating profits divided by total assets, $Size_{fit}$ is natural logarithm of total assets, and $Tang_{fit}$ is tangible assets divided by total assets. $IndLev_{it}$ is industry median leverage, calculated at the 3-digit NAICS to avoid collinearity with skill and mobility measures, which are at the 4-digit NAICS.

Table 4 presents the results. Columns 1 and 2 present the OLS and fixed effect estimations using the specification in Equation 11. OLS results are reassuring because they show that this relation is not just a within firm and industry effect (picked up in the fixed effect regressions) but it holds generally across the universe of firms. The estimated coefficients on the interaction term is significantly negative, showing that higher labor mobility when the workforce is skilled decreases firms' leverage. The coefficients on the other firm characteristics are consistent with previous studies.

Including the fixed effects in the previous regressions accounts for time series and cross sectional correlations in the explanatory variables, and leads to consistent estimation of the coefficients and correct standard errors (Petersen, 2009). However, there is a concern that the persistence in the skill and mobility measures may cause the spurious regression bias, i.e. reporting significant links between variables that are in fact independent (Phillips, 1986; Granger IV, Hyung, and Jeon, 2001). Furthermore, as shown in Figure 1, most of the variation in the skill and mobility variables are from between industries. To ensure that the estimations are indeed capturing the economic forces, I also test this relationship in the following two cross sectional specifications.

First, I take time-series averages of all the variables for each firm, and then run a cross-sectional regression of

$$\begin{aligned} \bar{Lev}_f =& \beta_1 \bar{Skill}_i * \bar{Mobility}_i + \beta_2 \bar{Skill}_i + \beta_3 \bar{Mobility}_i + \beta_4 \bar{Q}_f \\ &+ \beta_5 \bar{Profit}_f + \beta_6 \bar{Size}_f + \beta_7 \bar{Tang}_f + \beta_8 \bar{IndLev}_f + \varepsilon_f \end{aligned} \tag{12}$$

where the upper bar shows the average over time for each variable at each firm. Results of this specification is shown in column 3 of Table 4. This test purely captures the labor mobility channel in the cross section and the estimates of standard errors are immune to cross sectional correlations of the explanatory variables (Cochrane, 2009). Finally, I also test the link between leverage and labor characteristics in the cross section in the spirit of Fama and MacBeth (1973). Results of this test is shown in column 4. Interestingly, the magnitude of estimated coefficients in the cross sectional tests are much larger than fixed effect estimates.

Columns 1 to 4 of Table 4, consistently estimate a negative coefficient on the interaction term of skill and mobility. This shows the negative effect of firms' reliance on skilled labor with high mobility on its leverage choice. Probably, the estimates in columns 3 and 4 are more reliable to give a sense of the economic magnitude of the link. Based on the cross sectional estimations in column 3, a one standard deviation increase in labor mobility leads to a 19.44% decrease in net book leverage of high skilled firms. Here, a high skilled firm is defined as a firm whose skill is one standard deviation above the average skill.

Controlling for tangibility in the regressions is particularly important to rule out an alternative explanation. If having a skilled and mobile workforce corresponds to less tangible capital in the data, then it is natural to think that firms with skilled and mobile workers have lower leverage in equilibrium because they have less pledgeable assets. However, by controlling for tangibility in the tests we examine the effect of labor characteristics on top of any pledgeability effect.

To ensure that the above results do not just pick up the industry effects, I repeat the tests using the firm-level skill and mobility in the airlines' sample. In the airlines tests I drop market to book value from the right-hand side, because not all of the airlines in my sample are publicly traded. Equation 13 outlines the specification with skill and mobility measured at the firm-level (thus the subscript f).

$$\begin{aligned} Lev_{fit} =& \alpha_f + \gamma_t + \beta_1 Skill_{fit} * Mobility_{fit} + \beta_2 Skill_{fit} + \beta_3 Mobility_{fit} + \beta_4 Profit_{fit-1} \\ & + \beta_5 Size_{fit-1} + \beta_6 Tang_{fit-1} + \beta_8 IndLev_{fit-1} + \varepsilon_{fit} \end{aligned} \tag{13}$$

Results of the test using the firm-level skill and mobility are shown in columns 5 and 6 of Table 4. The estimations are consistent with the previous specifications, showing that labor mobility in more skilled firms has a negative and significant impact on leverage. Note that there is a fair amount of variation in skill and mobility measures across airlines, stemming from differences in their business models (outsourcing, etc.).[7]

Investment. Next, I examine the effect of skilled labor mobility on firm's investment. The main structure of the investment tests are similar to the leverage tests, only the left hand

[7]For instance, unlike many other airlines, Virgin America uses contractors (instead of employees) for baggage delivery, heavy maintenance, reservations, catering, etc. The differences in business models of airlines leads to differences in the composition of skill and mobility of their workforce.

side variable is replaced with the investment rate. Note that the right-hand side controls are consistent with the investment literature, including Tobin's Q (Q_{fit}) and cash flows ($Profit_{fit}$).

Table 5 presents the results of investment tests. Columns 1 to 4 show the estimation results for OLS, fixed effects, cross sectional tests using firm averages, and Fama-MacBeth regressions, respectively. All the specifications consistently estimate a statistically significant negative coefficient on the interaction term. This means that in the data, firms with a more skilled and mobile workforce invest at lower rates. The economic magnitude of the impact on investment is also large. Based on the cross sectional estimation in column 3, a one standard deviation increase in mobility is associated with 5.48% lower investment in skilled firms.

Note that I do not conduct the investment regressions on the airline sub-sample using the firm-level measures of skill and mobility. The main reason is that most of the airlines in my sample are not publicly traded, so they lack a measure of Tobin's Q, which is critical to identification of any effect in investment regressions.

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Figure 1: Variation in Skill and Mobility Over Time for Select Industries

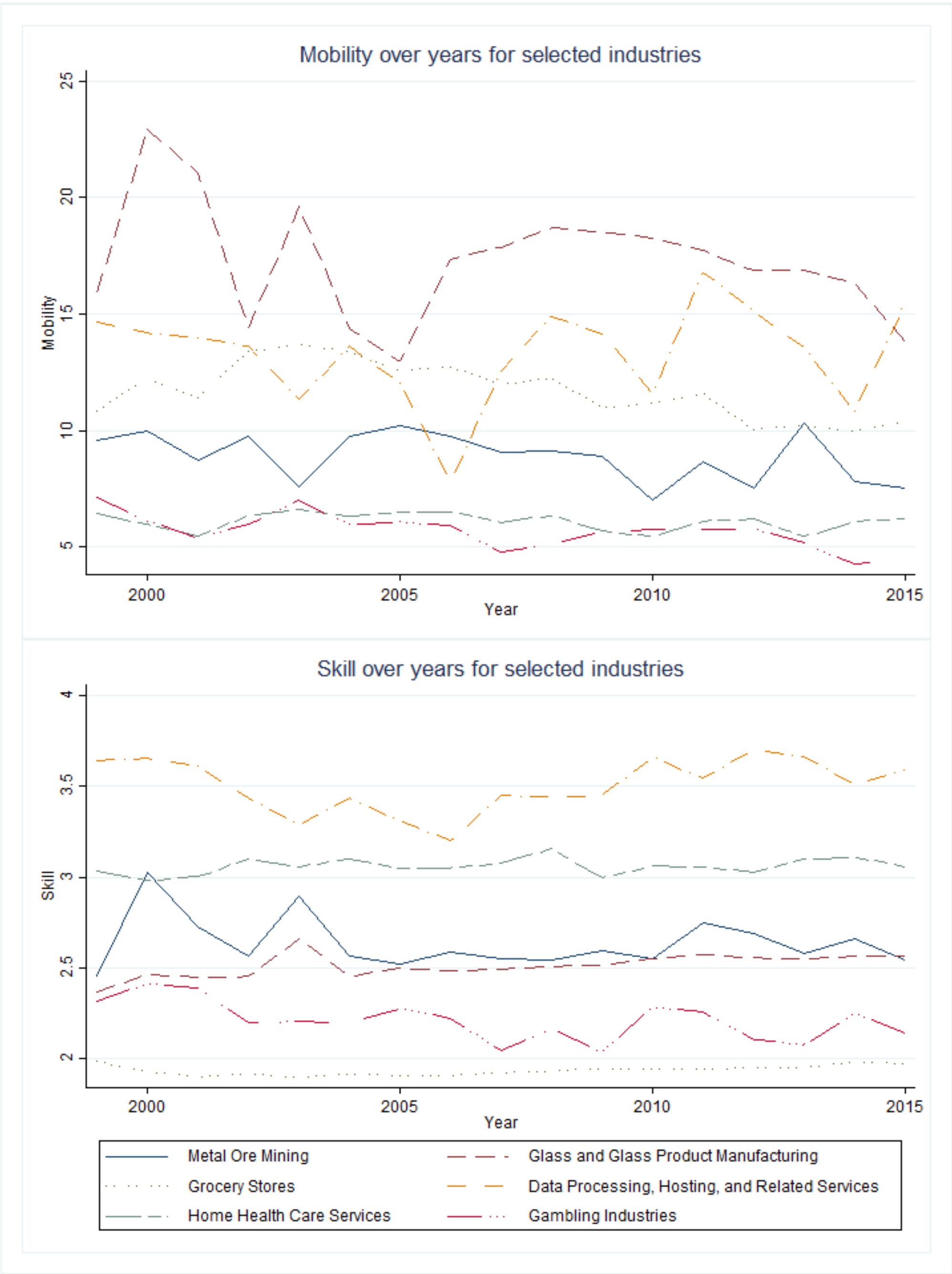

Table 1: Elasticity of Moments with respect to Parameters

This table reports the elasticity of moments to the model parameters. This table could be created using each set of estimated parameters in Table 1 in the main paper. I use the parameters estimated for the high skill firms. Blank entries indicate an elasticity of less than 0.5 in absolute value. The elasticities are calculated around the estimated parameters, and over a window with a range of 20% (10% deviation on each side) of the estimated value of each parameter. Reading: Around the SMM estimate, a 1% increase in δ_k is associated with a 1.09% increase in the average investment rate in simulated data.

	α	ν	ρ	σ	δ_k	c_k	c_l	ξ	m	θ
Mean investment/assets	0.59	0.81			1.09					
Mean net leverage	-1.65	-0.73			-0.66	-0.90		-0.74		0.60
Mean income/assets		-1.17								
Mean distribution/assets	0.78									-0.77
Mean wage bill/assets										
Mean wage bill/income		0.84								
SD investment/assets	0.88	0.52		0.72		-1.07				
SD leverage	-0.76					-0.61			0.68	0.73
SD income/assets		-0.86	0.55	0.81						
SD distribution/assets	0.53	-0.66		-0.58						
SD wage bill/assets									0.55	
SD wage bill/income		0.94	0.64						0.92	-0.68
SD employment growth		1.19					-0.85			-0.59
AC(1) leverage			0.82						-0.76	-0.62
AC(1) log(income)			0.87							

Table 2: Labor mobility and firm policies: net book leverage, pure debt leverage, and cash

This table shows the impact of labor mobility on leverage and cash holdings using the instrumental variable regressions with the firm-level variable IDD_{ft} as shocks to labor mobility Mob_{ft}. The dependent variables are net book leverage (i.e., net debt/assets), pure debt leverage (i.e., total debt/market value of assets), and cash ratio (i.e., cash and cash equivalents/assets). Subscript f shows that the variable is measures at the firm level, and subscript t indexes time in years. Standard errors in parentheses are clustered at the firm level. The *, **, and *** symbols denote statistical significance at 10%, 5%, and 1% levels.

Test:	Net Book Leverage		Pure Debt Leverage		Cash Ratio	
IV Stage:	1st	2nd	1st	2nd	1st	2nd
Dep. Variable:	Mob_{ft}	$Bk.\ Lev_{ft}$	Mob_{ft}	Lev_{ft}	Mob_{ft}	$Cash_{ft}$
	(1)	(2)	(3)	(4)	(5)	(6)
IDD_{ft}	-0.010*		-0.012**		-0.012*	
	(0.006)		(0.006)		(0.007)	
$IDD_{ft} \times High\ Skill_f$	-0.059***		-0.051***		-0.061**	
	(0.019)		(0.014)		(0.025)	
$\widehat{Mob}_{ft}$		-0.013		-0.021		0.015
		(0.015)		(0.019)		(0.028)
$\widehat{Mob}_{ft} \times High\ Skill_f$		-0.096***		-0.070**		0.009*
		(0.029)		(0.032)		(0.005)
1st Stage $F-$stat.	44.01		47.11		38.98	
$Controls_{f,t-1}$	Y	Y	Y	Y	Y	Y
$Controls_{f,t-1} \times High\ Skill_f$	Y	Y	Y	Y	N	N
Firm & Year FE	Y	Y	Y	Y	Y	Y
N	10,166	10,166	11,773	11,773	6,396	6,396
adj. R^2	0.055	0.069	0.063	0.079	0.048	0.032

Table 3: Occupations and Industries In a Skill and Mobility Sort

Panel A shows occupations with the highest and lowest average concentration, separately for high skill and low skill groups. The concentration measure is based on dispersion of a job across industries (see Equation 9). Panel B presents industries (4-digit NAICS) with the lowest (bottom 5) and highest (top 5) average mobility, separately for high skill and low skill groups. The mobility measure is the inverse of the weighted average of concentration for all occupations in each industry (see Equation 10).

Panel A: Occupations

	Highest Concentration		Lowest Concentration	
	Job Code	Job Title	Job Code	Job Title
Low Skill	53-4031	Railroad Conductors	43-9021	Data Entry Operators
	37-2021	Pest Control Workers	51-2092	Assembly Line Machine Operator
	51-9197	Tire Builders	51-1011	Supervisors of Prod./Operating Workers
	39-3021	Motion Picture Projectionists	43-5032	Dispatchers
	39-5092	Manicurists and Pedicurists	43-3051	Payroll and Timekeeping Clerks
High Skill	25-1066	Psychology Teachers, Postsecondary	15-2031	Operations Research Analysts
	53-2011	Airline Pilots, and Copilots	27-1027	Set and Exhibit Designers
	27-3021	Broadcast News Analysts	13-1161	Market Research/Marketing Analysts
	29-1131	Veterinarians	17-2141	Mechanical Engineers
	17-1022	Surveyors	11-3051	Industrial Production Managers

Panel B: Industries

	Lowest Mobility		Highest Mobility	
	NAICS	Industry	NAICS	Industry
Low Skill	4531	Florists	4481	Clothing Stores
	7132	Gambling Industries	4471	Gasoline Stations
	5617	Services to Buildings and Dwellings	4522	Department Stores
	3131	Fiber, Yarn, and Thread Mills	3273	Cement and Concrete Product Manufacturing
	4842	Specialized Freight Trucking	4421	Furniture Stores
High Skill	6215	Medical and DiagNstic Laboratories	5415	Computer Systems Design and Related Services
	6111	Elementary and Secondary Schools	5511	Management of Companies and Enterprises
	5411	Legal Services	5181	Data Processing, Hosting, and Related Services
	5151	Radio and Television Broadcasting	3345	Navigational and Control Instruments Manufact.
	6223	Specialty Hospitals	3341	Computer and Peripheral Equip. Manufacturing

Table 4: Mobility of Skilled Labor and Firms' Capital Structure

This table summarizes the results of leverage regressions on labor skill, mobility and firm characteristics. Columns 1 to 4 run the test when skill and mobility are measured at the industry level (SIC3/NAICS4). They show the results for OLS, fixed effects, cross sectional tests using firm averages, and Fama-McBeth regressions, respectively. Columns 5 and 6 repeat the tests for the airlines sub-sample, for which I compute firm-level measures of skill and mobility. Standard errors in parentheses are clustered at the firm level. The *, **, and *** symbols denote statistical significance at 10%, 5% and 1% levels.

	Dependent Variable: Net Book Leverage					
	All Firms				Airlines	
	OLS (1)	FE (2)	XS (3)	F-MB (4)	FE (5)	F-MB (6)
Skill * Mobility	-0.012***	-0.004***	-0.013***	-0.011***	-0.025**	-0.241**
	(0.001)	(0.001)	(0.002)	(0.001)	(0.010)	(0.103)
Skill	0.060***	0.058***	0.070***	0.061***	0.190	0.279
	(0.019)	(0.019)	(0.020)	(0.010)	(0.189)	(0.294)
Mobility	0.035***	0.010***	0.045***	0.033***	0.087**	0.688*
	(0.004)	(0.003)	(0.005)	(0.003)	(0.033)	(0.366)
Tobin's Q	-0.035***	-0.005***	-0.046***	-0.054***		
	(0.002)	(0.001)	(0.003)	(0.004)		
Profitability	0.222***	-0.010	0.258***	0.220***	0.025	-0.306**
	(0.016)	(0.017)	(0.019)	(0.017)	(0.050)	(0.114)
Size	0.054***	0.098***	0.043***	0.053***	0.124**	0.025***
	(0.002)	(0.005)	(0.002)	(0.002)	(0.057)	(0.008)
Tangibility	0.378***	0.372***	0.426***	0.367***	0.341**	0.388***
	(0.017)	(0.025)	(0.018)	(0.013)	(0.135)	(0.110)
Industry Leverage	0.316***	0.262***	0.344***	0.207***		
	(0.043)	(0.044)	(0.031)	(0.012)		
Firm FE	N	Y	N	N	Y	N
Year FE	N	Y	N	N	Y	N
Observations	55,150	55,150	8,849	55,150	555	555
R-squared	0.354	0.079	0.432	0.365	0.187	0.403

Table 5: Mobility of Skilled Labor and Firms' Investment

This table summarizes the results of investment regressions on labor skill, mobility and firm characteristics. The skill and mobility variables are measured at the industry level (SIC3/NAICS4). Columns 1 to 4 show the results for OLS, fixed effects, cross sectional tests using firm averages, and Fama-McBeth regressions, respectively. Standard errors in parentheses are clustered at the firm level. The *, **, and *** symbols denote statistical significance at 10%, 5% and 1% levels.

	Dependent Variable: Investment Rate			
	OLS	FE	XS	F-MB
	(1)	(2)	(3)	(4)
Skill * Mobility	-0.0008***	-0.0002*	-0.0008***	-0.0009***
	(0.0002)	(0.0001)	(0.0003)	(0.0002)
Skill	0.0235***	0.0051*	0.0315***	0.0249***
	(0.0036)	(0.0023)	(0.0042)	(0.0024)
Mobility	0.0015**	0.0004*	0.0020**	0.0019***
	(0.0007)	(0.0002)	(0.0009)	(0.0006)
Tobin's Q	0.0044***	0.0029***	0.0023***	0.0058***
	(0.0003)	(0.0003)	(0.0004)	(0.0004)
Profitability	0.0587***	0.0574***	0.0171***	0.0629***
	(0.0025)	(0.0036)	(0.0035)	(0.0050)
Size	0.0002	-0.0104***	0.0015***	0.0002
	(0.0003)	(0.0012)	(0.0004)	(0.0002)
Tangibility	0.1200***	-0.0630***	0.1660***	0.1200***
	(0.0042)	(0.0091)	(0.0051)	(0.0055)
Firm FE	N	Y	N	N
Year FE	N	Y	N	N
Observations	42,843	42,843	8,133	42,843
R-squared	0.155	0.046	0.271	0.154