Heterogeneous Passthrough from TFP to Wages*

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Abstract

We examine the passthrough of firms' productivity shocks to hourly wages using rich matched employer-employee data, allowing us to control for endogenous worker mobility and unobserved worker heterogeneity. We find an average passthrough of 0.08 which is economically and statistically significant. Hourly wages are twice as responsive to negative shocks as to positive shocks–especially during recessions. Ignoring endogenous labor mobility underestimates passthrough, erroneously implying downward wage rigidity.

Keywords: wage setting, productivity, passthrough, income risk, firm shocks, market power, TFP.

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1 Introduction

How do fluctuations in firms' idiosyncratic productivity affect workers' wages? How and why does this vary over time and across firms and workers with different characteristics? The answers to these questions are important for understanding how employers differ in their ability to set wages (Berger et al., 2022), why workers with similar characteristics receive different salaries across firms (Abowd et al., 1999), and the role of firms' shocks in determining workers' income instability (Barth et al., 2016), among others.

In this paper, we use administrative matched employer-employee panel data covering the entire private sector of Denmark to provide new evidence on the elasticity of workers' hourly wages with respect to firms' productivity shocks. We refer to this elasticity as "passthrough". There is a substantial literature that estimates this passthrough elasticity, building largely on early work by Guiso et al. (2005) and others.[1] In general, this literature has focused on incumbent workers who remain at the firm in consecutive periods (i.e., stayers). This approach might lead to biased estimates of passthrough if workers switch jobs *in response* to a change in firm productivity and wages (i.e., if labor supply and demand curves are functions of productivity and wages).

To highlight the importance of worker mobility, we exploit the richness of our data to estimate workers' probability of staying at a firm as a function of their own and their employer's characteristics, as well as a set of family-related variables: their marital status, the observable characteristics of their spouse, and the characteristics of the spouse's employer, including the idiosyncratic productivity shocks received by the firm where the spouse works. The underlying assumption is that these family-related observables will affect a worker's job mobility decisions, but not the elasticity of wages to productivity in their own firm. Secondly, we directly analyze the impact of firms' productivity on worker mobility and the wage changes experienced by workers who move between firms (i.e., switchers). We find that considering endogenous worker mobility greatly changes the estimated impact of idiosyncratic firm shocks, especially if these shocks are negative.

To estimate firm productivity shocks, we leverage the firm- and worker-level informa-

[1] See Manning (2020), Card et al. (2018), and Guiso and Pistaferri (2020) for recent surveys.

tion available in our data to estimate firm-level Total Factor Productivity (TFP) non-parametrically while allowing for arbitrary labor supply and adjustment frictions. This framework, developed in Chan et al. (2025), extends the non-parametric approach of Gandhi, Navarro and Rivers (2020) to allow for imperfect competition in labor markets and for observed and unobserved heterogeneity in the quality of the labor input.[2]

Our main empirical analysis consists of a series of worker-level panel regressions that relate log hourly wage growth for stayers (i.e., workers who stay in the same firm for at least two consecutive periods) to different measures of shocks to firm productivity. We reach five main results. First, we find a passthrough elasticity of hourly wages to changes in overall TFP of 0.08. This implies that a full-time worker employed at a firm that experiences a one-standard-deviation change in TFP receives a change in hourly wages equivalent to \$1,075 of annual earnings in US dollars, or around 1.8% of the average annual salary in Denmark. These wage changes are long-lasting, with passthrough from persistent TFP shocks remaining undiminished for four years after the shock. Considering that, in a typical year, around 20% of the firms in our sample (which employ around 25% of all private-sector workers in Denmark) experience a productivity change of at least one standard deviation from the mean, we conclude that fluctuations in firm productivity have important implications for workers' wages.

Second, we find that the passthrough is asymmetric in that the elasticity of workers' wages to a negative change in productivity is almost twice as large as the elasticity to a positive change. Quantitatively, an increase in productivity of one standard deviation generates an increase in annual earnings of \$840 (1.4% of the average annual salary), whereas a decrease in productivity of the same magnitude generates a decline in annual earnings of \$1,580 (2.6% of the average annual salary). Hence, workers are more exposed to negative than to positive changes in firm productivity.

[2] Although our estimation approach builds on the methodology developed in Chan et al. (2025), the focus and contributions of this paper are substantively different. The primary objective of this paper is to estimate worker-level passthrough from firm productivity shocks to hourly wages using matched employer-employee data, with a particular emphasis on heterogeneity and asymmetry in passthrough elasticities and in the bias induced by endogenous worker mobility. In contrast, Chan et al. (2025) focus on decomposing wage markdowns into components arising from adjustment costs and labor market power. They conduct their analysis entirely at the firm level and primarily use estimates of passthrough (among other tools) to infer the nature of labor market frictions and firm dynamics.

Third, workers' endogenous mobility plays an important role in shaping the impact of firms' shocks on wages. We show that selection into and out of continued employment biases the passthrough coefficient toward zero, especially for negative shocks. In fact, if we were to ignore workers' mobility, we would erroneously conclude that there is significant downward wage rigidity and that the wage elasticity to positive shocks is almost twice the elasticity to negative shocks, which is the opposite of what we find in our baseline results. We derive expressions for the selection mechanism arising in a simple discrete choice model of labor supply to provide intuition for the direction and magnitude of the bias. The theory predicts that the bias is increasing in the passthrough elasticity, which we confirm in the data. This result highlights that these elasticities should be interpreted as the within-firm passthrough of TFP to a *latent* hourly wage rate, since our approach accounts for the unobserved wage offers rejected by workers who leave firms in response to TFP shocks.[3]

Fourth, we show that the passthrough is heterogeneous and varies considerably across firm and worker characteristics and over the business cycle. On the firm side, we find lower passthrough among large, high-productivity, and high-market-share firms relative to small and low-productivity firms. These findings are consistent with the predictions of models where firms have labor market power (for example, Berger, Herkenhoff and Mongey (2022) or Yeh, Macaluso and Hershbein (2022)). On the worker side, we find that high-income workers experience higher passthrough than low-income workers, especially from negative shocks, which is consistent with high-income workers having a higher proportion of performance pay in their earnings. Similarly, we find that the wages for older and long-tenure workers increase more after a positive productivity shock and decline less after a negative shock than those of young and recently hired workers. Finally, we find that during recessions, the passthrough from positive productivity shocks collapses to zero, whereas the passthrough from negative shocks remains almost unaltered.

Finally, we focus on workers who switch firms between periods. We find that negative firm productivity shocks increase a worker's probability of leaving a firm and switching to another employer (with a mean separation elasticity of -2.39), whereas positive productivity

[3] This is the relevant elasticity when considering, for example, equilibrium models of the labor market where firms face an upward-sloping labor supply curve.

shocks have a much smaller effect on outward worker mobility (a mean separation elasticity of -0.72). This is consistent with models where firms move along labor supply curves in response to productivity shocks, and also with the idea that workers use job mobility as a form of self-insurance against negative income shocks. We also find that among switchers, the average wage change is positive, regardless of whether the firm they left experienced positive or negative productivity growth. This supports the interpretation that many workers switch jobs endogenously to avoid wage cuts, rather than being involuntarily displaced, as displacement is typically associated with negative wage changes. Wage growth is lowest for switchers leaving firms that experienced large negative productivity shocks: the larger the decline in firm productivity, the smaller the average wage gain for these switchers. This suggests that as negative shocks intensify, a greater share of workers leave involuntarily — consistent with lower re-employment wage outcomes. In contrast, for workers leaving growing firms (those with positive productivity shocks), wage growth from switching is relatively stable and does not vary with the magnitude of the (old) firm's productivity increase.

Passthrough Theory. Before proceeding, it is useful to consider when, and to what extent, we should expect firms to transmit productivity shocks to workers' wages. The answer depends on the economic environment. In a frictionless, perfectly competitive labor market where with price-taking firms, idiosyncratic firm productivity shocks do not affect wages, implying zero passthrough. Deviating from the frictionless and competitive framework, passthrough will no longer be zero, and the nature and magnitude of passthrough will depend on the mechanisms of market imperfection. For example, consider a standard market power model where firms move up and down upward-sloping labor supply curves in response to idiosyncratic productivity shocks. In such an environment, the passthrough elasticity will be positive as firms that become more (less) productive will increase (decrease) wages in order to move up (down) their labor supply curve and employ more (fewer) workers.

Passthrough may also depend on the nature of production and competition in the labor market. For example, if atomistic firms operate with homogeneous output and labor supply elasticities (for example, a Cobb-Douglas production function and log-linear labor supply curve), the passthrough elasticity will be a positive scalar common to all firms in the market (as in Lamadon et al. (2022)) and will not depend on firm size or the sign of the shock.

However, if firms operate heterogeneous production technologies, or have oligopsony power in labor markets (as in Berger et al. (2022)), we will see heterogeneity in passthrough elasticities.[4] Other market imperfections can also generate heterogeneous passthrough elasticities. For example, if firms face hiring and firing costs, asymmetry in these costs will lead to asymmetry in passthrough. Differences in search frictions for different workers or firms may also lead to heterogeneity in passthrough elasticities. In this paper, we stay agnostic regarding the exact nature of market imperfections that firms may face, but rigorously measure the passthrough elasticity in a flexible setting which nests many such mechanisms. In this way, our framework can provide guidance for developing theories of wage setting and passthrough.

Another key implication of the aforementioned imperfect market model is that the estimation of passthrough may be complicated by selection bias even in the simplest of theoretical settings. For example, suppose workers choose jobs based on the wage and firm-level job amenities. Firms face a common labor supply elasticity such that equilibrium firm-level wages depend on productivity (observed) and job amenities (unobserved) with a common, constant, passthrough elasticity. Even if changes in productivity and amenities are uncorrelated in the firm population, workers will be more likely to endogenously leave firms that experience a drop in both factors, leading to a correlation between productivity and unobserved amenities in the sample of "stayers" in the data. Thus, ignoring endogenous worker mobility will result in a biased estimate of the passthrough elasticity. Appendix D derives the theory and intuition behind this selection bias using several examples in a discrete choice model of labor supply and wage setting. We also show that this bias will be increasing in the passthrough elasticity, since workers facing larger firm-level passthrough elasticities are more likely to be under-sampled (as they will be more likely to leave their firm in response to a given negative shock). We confirm the predictions of these theoretical results in our empirical application.

Finally, since our measure of TFP is implicitly "revenue" TFP (TFPR), we show that, in a simple model where firms face downward sloping demand with firm-level demand shocks,

[4]In Appendix E, we build a simple model which nests these different environments and derive the passthrough elasticity in each. We show, for example, that in a model with oligopsonistic firms and a simple logit labor supply model, the passthrough elasticity is decreasing in firm market share and is negatively asymmetric, which is consistent with our empirical findings.

passthrough from TFPR is an upper bound for passthrough of "quantity" productivity or efficiency (TFPQ). The share of passthrough due to TFPQ equals the inverse markup. Through this lens, standard estimates of markups (10–30%) imply that about 77–90% of passthrough from TFPR is due to TFPQ, with the remainder coming from demand shocks.

Related Literature. Our work contributes to the extensive literature that studies how firm-level shocks affect worker earnings. An early example is Guiso, Pistaferri and Schivardi (2005), who study the passthrough from firms' value-added shocks to wages and the degree of insurance provided by firms using matched employee-employer data from Italy. Their, and similar, methodologies have been implemented for multiple countries, including the US, delivering consistent results.[5] More recent work exploits quasi-experiments—derived from patent approvals (Kline et al., 2019), government grants (Howell and Brown, 2020) and procurement auctions (Carvalho et al., 2023)—to identify the passthrough of positive revenue shocks for a select subset of firms.

Relative to this literature, our methodology allows us to provide estimates of passthrough for both positive and negative TFP shocks across the entire private sector, controlling for worker mobility and unobserved worker quality. The results that the passthrough is negative asymmetric shows that, rather than fully insuring workers against negative risk, firms are unable or unwilling to smooth income during downturns, effectively transferring idiosyncratic risk to the workers' wages and employment status. A critical benefit of using structural estimates of TFP is that it allows us to provide estimates of passthrough elasticities which do not confound the endogenous response of wages to exogenous productivity shocks with the equally endogenous response of firm revenues (or value-added per worker) to productivity shocks. A few other papers have also used TFP as their measure of the firm shock (notably Carlsson et al. (2015)), but do not separately identify TFP from worker quality or correct for endogenous mobility, which we show are both important for our results.

Ours is not the first paper to examine how passthrough varies with the sign of the firm shock. Juhn et al. (2018) study the passthrough from (residualized) firm revenue changes to

[5] See for instance Berger et al. (2022), Souchier (2023), Friedrich et al. (2021), Carlsson et al. (2015), Garin and Silvério (2022), Guertzgen (2014), Ai and Bhandari (2021), Rute Cardoso and Portela (2009), Barth, Bryson, Davis and Freeman (2016), Juhn, McCue, Monti and Pierce (2018), Balke and Lamadon (2022), Lamadon et al. (2022), Maibom and Vejlin (2021), Carvalho et al. (2022), among others.

worker annual earnings, finding little asymmetry in passthrough. We show that controlling for endogenous mobility is crucial for estimating passthrough asymmetry and demonstrate that using hourly wages isolates the effect of productivity on pay independent of hours worked. We share the interest in controlling for endogenous mobility with Friedrich et al. (2021) who also account for worker mobility while estimating passthrough elasticities. Relative to their approach, we are able to leverage detailed firm-, individual-, and household-level information to estimate and control for worker mobility.

Finally, our productivity estimation method extends the non-parametric approach of Gandhi, Navarro and Rivers (2020) by additionally allowing for dynamic labor adjustment costs and labor market power in wage setting. We control for unobserved variation in the quality of the labor input using a two-way fixed effects approach, building on Abowd et al. (1999) and Bagger et al. (2014).

The rest of the paper proceeds as follows. In Section 2, we introduce our data sources and discuss our sample selection and in Section 3 we present our estimation strategy. Section 4 discusses our baseline results. Section 5 studies how passthrough varies across firms and workers with different characteristics, whereas Section 6 studies how worker labor mobility between firms with different productivity levels affects wages. Section 7 concludes.

2 Data and Institutional Background

In this section, we briefly describe the data sources and sample selection. Additional details and the full list of the variables used in our analysis can be found in Appendix A. Our main source of information is a matched employer-employee administrative data set from Statistics Denmark covering the years 1991 to 2010. Worker and firm characteristics are measured in November of each year. We obtain worker-level information from the Integrated Database for Labor Market Research, which is an annual database containing employment and demographic information for the entire population of Denmark. From this data set, we obtain several key variables such as annual income and hourly wages for each job at which an individual worked during the year, total number of hours and days worked in each job, occupation, labor market status, position within the firm (e.g., manager, skilled/unskilled labor), age, gender, education, and tenure within the firm. Our data also contains an identifier that links workers with their spouse. This information is useful when estimating the first stage of the selection model described in Section 3.2. Our main outcome variable is the log change in individual hourly wages (the sum of regular salary, bonuses, and overtime income at their primary job divided by the total number of hours worked at that job in a year). We use hourly wages instead of annual income to isolate the impact of a shock to firms' productivity on individual earnings from changes in hours worked during the year.

In the baseline sample we use to estimate worker ability and firm productivity, we consider workers who are 15 years and older, who are not working in the public sector, and who are not self-employed. We further restrict our passthrough estimation sample to full-time workers (defined as individuals who work 30 or more hours per week) whose annualized total labor earnings are above 30,000 (2010) Danish kroner so as to maintain workers with a high labor-market attachment.[6] These restrictions leave us with 8.98 million worker-year observations for our primary analysis.[7]

We match this individual-level panel to a firm-level panel—the Firm Statistics Register—which contains annual accounting and input use data for the universe of the Danish private sector.[8] The key firm-level variables we use are annual revenue (sum of revenue from sales, capital gains, other operating income, and changes in inventories), capital stock, expenditure on intermediate inputs and materials, and employment (in full-time equivalents), as well as firm age, geographic location, and industry (NACE codes). We discard firms with non-positive or imputed measures of sales, employment, and other key variables. We also discard firms that have less than three years of data since the TFP estimation procedure uses lags of input variables to recover productivity levels, and our passthrough analysis requires at least two observations of firm-level productivity to calculate "shocks" to productivity. This leaves us with around 45,000 firms per year, most of which have been in operation for at least 10

[6]This cutoff is in real kroner which converts to about 4,600 US dollars in 2010.

[7]To avoid the disclosure of sensitive information, all percentiles reported in this paper are calculated as the mean of the two adjacent milliles. For example, to calculate the median of a variable, we divide the distribution into 1000 quantiles and report the mean of the pooled 500th and 501st quantiles. We also round up the sample size to the nearest 000s when appropriate.

[8]The Firm Statistics Register begins with manufacturing in 1995 and gradually adds other sectors, reaching universal coverage of the Danish economy in 2001. Our results do not change in any substantial way if we consider data starting in 2001.

years. Table B.1 shows summary statistics of our sample of workers and firms.

Danish Labor Market. The Danish labor market is characterized by lax employment protection, generous unemployment insurance, and active participation of firms, workers, and the government in the promotion of employment. Relative to other European countries, the low barriers to firing and hiring workers in Denmark and the presence of a safety net for unemployed workers—a system that has been called "flexicurity" (Andersen and Svarer, 2007)—have generated a resilient labor market with high turnover that keeps unemployment spells short even during periods of economic distress (Andersen, 2021).[9] Similarly, wage flexibility has been relatively high compared with other countries despite the fact that labor unions (that cover more than three quarters of all workers in Denmark), firms, and the government interact to determine wage-setting policies. For the vast majority of workers, wages are set at the worker-firm level, with centrally bargained contracts limited to determining working conditions and wage floors for low-skill workers (Dahl et al., 2013). In summary, although the Danish labor market is unique in many ways, the degree of flexibility in wage formation and worker mobility (similar to the US) makes it a relevant economy to study the relation between firm productivity and worker wages.[10]

3 Empirical Strategy

This paper builds on the framework of Gandhi et al. (2020) (GNR hereafter) and Abowd et al. (1999) to obtain estimates of firm productivity and wages controlling for unobserved worker ability and wage/employment dynamics. Our empirical approach is similar to Chan et al. (2025), with the exception that estimating passthrough at the worker level—as we do in this paper—requires correcting for endogenous mobility. In this section, we briefly outline the framework and how we apply it in our setting, focusing on how this paper innovates relative

[9] Botero et al. (2004) finds that the Danish labor market is one of the most flexible. In fact, in our data the rate of labor churn in Denmark, a measure of the dynamism of the labor market (Decker et al., 2016), is about 22%, which is higher than the 16% observed in the United States according to the US Census Business Dynamics Statistics data.

[10] Leth-Petersen and Sæverud (2021) characterize the distribution of labor earnings in Denmark. Among prime-age male workers, the authors find a mild increase in the P90/P10 labor earnings ratio from 1.2 to 1.3 between 1987 and 2008. The Great Recession generated a significant increase in inequality, with a P90/P10 ratio increasing up to 1.55 in 2009, followed by a further increase to 1.65 in 2017. A significant fraction of this rise in inequality is due to a widening of the P90/P50 labor earnings ratio.

to the literature. We then discuss our approach to estimating worker-level passthrough and how we account for endogenous worker mobility to correct for the associated selection bias.

We consider an environment with a continuum of workers (indexed by i) and a finite set of firms (indexed by j). Firms choose inputs to maximize the expected value of an infinite stream of discounted profits, subject to a (possibly firm-specific) upward-sloping labor supply curve and labor adjustment costs. We assume that firms are price takers in output and non-labor input markets, and firms face uncertainty about future productivity. This framework allows us to recover the full distributions of firm productivity and worker ability without assuming the parametric form of the production, labor supply, or adjustment cost functions.

3.1 TFP Estimation

We measure firm-level (revenue) productivity shocks building on the flexible estimation method proposed by GNR. Our approach departs from GNR in three key ways. First, we allow labor inputs to adjust dynamically in response to productivity shocks, subject to adjustment costs. Second, we allow firms to have wage-setting power in imperfect labor markets. Third, we use detailed data on individual wages, employment, and demographics to separately identify unobserved variation in labor quality from variation in firm productivity.

The main challenge in this step is to ensure that the productivity estimation method is consistent with the analysis in the rest of the paper. In particular, we need to recover firms' TFP without relying on the assumption that labor markets are perfectly competitive or that firms are price-takers in the labor market, as both preclude the possibility of passthrough from idiosyncratic productivity shocks to wages. We also cannot assume that labor is a "predetermined" input like capital, since our empirical analysis hinges on the observation that labor inputs adjust in response to contemporaneous productivity shocks.[11]

With these considerations in mind, we start by examining a general representation of a firm-level gross production function,

$$y_{jt} = f\left(k_{jt}, \ell_{jt}, m_{jt}\right) + \nu_{jt}, \tag{1}$$

[11] Furthermore, we avoid parametric assumptions (e.g., Cobb-Douglas or CES) because they impose specific productivity-input relationships that can affect passthrough estimates. This is crucial when exploring asymmetry and heterogeneity in the productivity-wage link across firm and worker characteristics.

where y_{jt} is log firm output and the variables k_{jt}, ℓ_{jt}, and m_{jt} are the log-levels of the capital stock, labor, and intermediate inputs. The ν_{jt} is the Hicks-neutral total factor productivity of firm j in period t. We assume that $\nu_{jt} = \omega_{jt} + \epsilon_{jt}$, where ω_{jt} is the persistent component of firm productivity, which is assumed to follow a first-order Markov process given by $\omega_{jt} = \mathbb{E}[\omega_{jt}|\omega_{jt-1}] + \eta_{jt}$, η_{jt} is an i.i.d. shock to the persistent component of firm productivity, and ϵ_{jt} is an i.i.d. ex-post transitory shock that is uncorrelated with input adjustments. In what follows, we use the terms persistent shock and transitory shock to refer to η_{jt} and ϵ_{jt}, respectively. We make several standard, but important, timing assumptions. Firms enter period t knowing K_{jt}, L_{jt-1}, and ω_{jt-1}. They then observe η_{jt} and choose L_{jt}, M_{jt}, and K_{jt+1}.[12] After the input choices are set, the firm observes ϵ_{jt}. We allow firms to adjust wages in response to ϵ_{jt}, but not inputs, and assume that firms are price-takers in output markets and the market for intermediate inputs.

We depart from GNR by allowing labor, L_{jt}, to be a dynamic input which may depend arbitrarily on η_{jt} and L_{jt-1} through returns to scale, adjustment costs, or other factors. Since this assumption does not alter the first-order conditions for the flexible input (M_{jt}), the standard GNR identification approach remains valid. This change only requires that we use lagged labor (rather than contemporaneous labor, as in GNR) as an instrument in the second stage to identify the output elasticities for labor and capital.

Since we do not observe output prices or quantities in our data, our measure of productivity captures "revenue" productivity (TFPR) rather than "quantity" productivity (TFPQ). This implies that variation in measured TFP may contain variation in production efficiency as well as in output demand (Syverson, 2011). We show in Appendix F that estimates of passthrough from TFPR can be seen as an upper bound for passthrough from TFPQ, and discuss implications for TFPQ passthrough when we discuss our results in Section 4.[13]

We allow the function $f(.)$ to represent a general and unknown relationship between inputs and output, subject to weak assumptions on differentiability and concavity, and estimate it non-parametrically, closely following the strategy outlined in Section V of GNR.

[12] Capital, K_{jt}, is a "predetermined" input that is fixed in period t, while intermediates, M_{jt}, is a flexible input chosen every period with no adjustment frictions. We use uppercase letters to denote levels of inputs.

[13] Consistent with this prediction, Carlsson et al. (2015) use Swedish manufacturing data with firm-level price indices and find evidence that passthrough to wages from TFPR is greater than from TFPQ.

We follow the literature (Syverson, 2011) and measure Y_{jt} as real revenues, K_{jt} as the real value of the capital stock (using the perpetual inventory method), and M_{jt} with the real value of materials and other intermediate input expenditures (such as energy and contract labor). The choice of labor input, which is at the center of our analysis, is discussed below. This approach allows for the recovery of the production function and firm productivity in the presence of unknown labor supply and adjustment costs.

Measuring Labor Input. The most straightforward approach to measuring the labor input used by the firm is to use total labor hours or the number of workers employed at the firm. Neither of these measures is ideal, however, as unobserved cross-sectional differences in the quality or composition of workers across firms will be loaded into the productivity term ν_{jt}. Similarly, changes in the quality of a firm's workforce over time, possibly driven by productivity shocks, will also be interpreted as changes in ν_{jt}.[14] Another possibility is to use the (real) wage bill of the firm. In this case, a firm that uses more high-skill workers relative to other firms will have a larger wage bill, potentially capturing differences in workers' ability (as in Fox and Smeets (2011)). However, this approach implicitly assumes that wages are perfectly correlated with worker ability and that labor markets are competitive conditional on ability, neither of which is appropriate in our context. In particular, if labor markets are perfectly competitive, we should not expect any passthrough from firms' *idiosyncratic* shocks to wages.

In this paper, we use data on hourly wages, individual characteristics, and employers to estimate the productive ability of each worker with a two-way fixed-effects regression similar in style to Abowd et al. (1999). In particular, we assume that workers are characterized by time-varying ability $A_{it} = A_i \times \Theta_t(X_{it})$, where A_i is the worker's unobserved time-invariant ability and $\Theta_t(X_{it})$ is a time-varying and log-linear function of the worker's time-varying observable characteristics, X_{it}. We further assume that the firm's labor input L_{jt} is the sum of the ability-weighted hours supplied by the workers employed at the firm, i.e., $L_{jt} = \sum_i A_{it} H_{ijt}$. These assumptions, along with an assumption that the firm faces a single labor supply curve, imply that each firm j pays its workers the same wage conditional on

[14] For example, if a software development firm replaces a full-time janitor with a full-time programmer, the firm's output will likely go up, but the number of hours or employees will remain fixed.

ability.[15] Hence, worker hourly wages (in logs) take the form $w_{ijt} = a_i + \theta_t(X_{it}) + \psi_{jt}$ where ψ_{jt} is the (log) ability price paid to each worker in firm j in period t. This provides the following estimating equation,

$$w_{ijt} = \underbrace{\alpha_i + X_{it}\Gamma_t}_{\text{Ability units}} + \underbrace{\psi_{j(i,t)t}}_{\text{Per-unit ability price}} + \xi_{ijt}, \tag{2}$$

where α_i is an individual fixed effect capturing unobserved worker ability, $X_{it}\Gamma_t$ captures the impact of observable characteristics on wages, $\psi_{j(i,t)t}$ is a firm-by-time effect that identifies the firm j in which worker i is employed in period t, and ξ_{ijt} is residual measurement error that is assumed to be uncorrelated with worker and firm characteristics. Using this specification, we are able to separately identify the component of hourly wages that is due to the fixed and time-varying characteristics of the worker—which we refer to as ability units—from the component of hourly wages that is due to differences across firms and time—which we refer to as the time-varying per-unit ability price paid by the firm. As in Card et al. (2013), we allow the parameters on individual observable characteristics, Γ_t, to vary with time to capture changes in the returns to education, occupation, or position within the firm.

Similarly to other papers in the literature (e.g., Barth et al. (2016), Song et al. (2019), and Engbom and Moser (2022)), we find that about 50% of the variance of w_{ijt} is accounted for by worker characteristics $\left(\hat{\alpha}_i + X_{it}\hat{\Gamma}_t\right)$, while 11% is accounted for by the firm effect.[16]

The estimated value of the individual fixed effect and the observable characteristics, denoted by $\hat{\alpha}_i + X_{it}\hat{\Gamma}_t$, is a measure of the "ability" of the worker, which we use to construct an "ability-adjusted" hourly wage as $\hat{w}_{ijt} = w_{ijt} - \hat{\alpha}_i - X_{it}\hat{\Gamma}_t$. Importantly, this measure of worker ability is independent of (but potentially correlated with) the characteristics of the firm that employs the worker (which are captured by a firm-time effect $\psi_{j(i,t)t}$). Using this

[15] This specification implicitly assumes that workers' characteristics do not affect their individual wage bargaining process within a firm. Workers all get the same share of the surplus within a firm conditional on ability. However, workers' characteristics can affect the wage bargaining process across firms, as we allow firm wage setting to depend on worker composition within a firm. For example, firms with higher ability workers on average may give a bigger share of their total surplus to all workers within the firm.

[16] We describe the estimation of the wage equation and identification of the firm-year effects in more detail, as well as addressing threats to identification such as limited mobility bias, in Appendix G.

measure for all workers in a firm, we construct the ability-adjusted labor input as

$$L_{jt} = \sum_{i \in J_t} \exp\left(\hat{\alpha}_i + X_{it}\hat{\Gamma}_t\right) H_{ijt},$$

where J_t is the set of workers in firm j in period t, and H_{ijt} is the number of hours worked by individual i in firm j in period t. Our ability-adjusted measure of firm productivity then comes from estimating the production function in Equation 1 where $\ell_{jt} = \log L_{jt}$.

Productivity Estimation Results. Our estimates of the production function (shown in Appendix Table B.3) are broadly consistent with the literature. We find mean output elasticities for capital, labor, and materials of 0.05, 0.35, and 0.54, respectively, with a mean returns to scale of 0.95. This is similar to what GNR find in Chilean and Colombian data, with the exception that our data spans the entire Danish private sector, including services, while most estimates of productivity (including GNR) are restricted to manufacturing. Persistent productivity (ω_{jt}) accounts for 78% of cross-sectional variation in TFP, and a third of variation in changes in TFP.

3.2 Estimating Passthrough with Endogenous Mobility

Having estimated firm productivity, we can now proceed to estimate the passthrough to wages. To do so, we specify the relationship between the change in a worker's hourly wage and productivity as

$$\Delta\hat{w}_{ijt} = \beta_0 + \beta^x x_{jt} + Z_{jt}\Gamma + X_{it}\Omega + \delta_t + \zeta_{ijt}, \tag{3}$$

where $\Delta\hat{w}_{ijt}$ is the change in the log hourly ability-adjusted wage of individual i in firm j between periods t and $t-1$, and x_{jt} is a measure of change in log productivity for firm j between periods t and $t-1$. The matrices Z_{jt} and X_{it} control for firm characteristics (lagged productivity, firm size, firm age, L_{jt-1}, and industry) and (lagged) worker characteristics (ability, experience, sex, age, tenure in the firm, wage level, and annual income), respectively, while δ_t is a time fixed effect that controls for aggregate fluctuations in the economy, and ζ_{ijt} is the residual. The coefficient β^x is our measure of the passthrough elasticity. In the following sections, we consider several different measures of x_{jt}, such as $\Delta\nu_{jt}$, η_{jt}, and ϵ_{jt}, and look at how the mean passthrough elasticity varies across different types of shocks, firms, and workers.

Much of our empirical analysis focuses on the impact of firm shocks on wages for workers who maintain a stable employment relationship with their firm, who we refer to as "stayers". However, a worker's decision to stay in a firm may depend on the shocks affecting the firm and the passthrough elasticity faced by the worker at that firm. Ignoring this endogenous selection in the sample might lead to biased passthrough estimates. For example, consider two firms that experience the same negative shock and decide to cut wages to reduce costs. If workers are more likely to leave a firm after experiencing a drop in wages and if the likelihood of leaving is higher for larger wage changes (both of which are consistent with the firm shedding workers while moving down its labor supply curve), then workers at both firms will be under-sampled relative to those at growing firms, and the firm with the larger passthrough elasticity will be especially under-sampled. We show in Appendix D how this will lead to classical selection bias when determinants of the wage are unobserved, and discuss intuition for the direction and magnitude of the potential bias. The key is that even if the passthrough residual term ζ_{ijt} is not correlated with productivity x_{jt} in the population, endogenous mobility will lead to correlation (and bias) in the sample.

To address this bias, we consider a standard selection model, as in Heckman (1979). We assume that the probability of worker i staying in firm j from period $t-1$ to t is given by $Pr(S_{ijt} = 1) = \Phi(U_{ijt}\xi^s)$, where $S_{ijt} = 1$ if worker i remains at firm j and U_{ijt} is a vector of worker and firm observable characteristics. Since our sample contains stayers and switchers (workers who exit the firm into other jobs or non-employment), we perform a simple two-step procedure by using a probit model to obtain estimates of $\hat{\xi}^s$ and then computing the inverse Mills ratio, denoted by $\hat{\lambda}_{ijt}$, which we include in our main regressions. Our passthrough estimates should thus be interpreted as the passthrough elasticity to a *latent* wage which includes both observed wage offers accepted by stayers, and the unobserved wage offers rejected by switchers. We see these elasticities as particularly informative about firms' internal wage setting policies rather than the reduced form effect on total worker income, though we also examine passthrough to other intensive and extensive margins affecting total income.[17]

To improve identification of the Mills ratio, we include additional observable variation in U_{ijt}, which determines the probability that workers will stay or leave their firm, but do not affect the elasticity of workers' wages relative to firm productivity should they choose to stay at the firm. We obtain such variation from the family linkages available in our data by creating, for each worker, a set of time-varying marital status indicators and—for those with working spouses—measures of their spouse's employment status and firm shocks. Specifically, we include indicators for marital status, separation, change of spouse, and spouse's employment status. This last term is interacted with other spousal information, including their log wage, change in log wage, firm TFP and log TFP change, age, experience, and whether or not the spouse stayed in their firm for that period. We exclude information about the spouse of a worker if the couple is working at the same firm. This gives us the following first-stage probit model,

$$\Pr(S_{ijt} = 1) = \Phi\left(\beta_p^s x_{jt} + \beta_n^s x_{jt} \times \mathbb{I}_{x_{jt}<0} + X_{it}\Omega^s + Z_{jt}\Gamma^s + T_{it}\Omega_m^s + E_{it} \times N_{it}\Psi^s\right), \qquad (4)$$

where x_{jt}, X_{it}, and Z_{jt} are as above, T_{it} is the set of marital status indicators, E_{it} is an indicator variable that equals 1 if the worker's spouse is employed and equals 0 if the spouse is not employed, and N_{it} is a vector of observables for the spouse and the spouse's firm, as described above.[18] The indicator function $\mathbb{I}_{x_{jt}<0}$ captures the asymmetric impact of positive and negative TFP shocks to the firm on the probability that a worker stays in the firm.

The assumption underlying our choice of instruments is that when a worker changes marital status, or their spouse has an income shock or employment change, this will affect the worker's decision to keep working at the current firm. However, conditional on staying at their firm, these changes do not affect the elasticity of wages to productivity in their own firm (i.e., that these spousal shocks are not embedded in ξ_{ijt}).[19] This requires that

[17] We also examine passthrough to hours and annual income in Table B.4, passthrough to mobility in Table II, and passthrough conditional on mobility in Table I, column 11.

[18] When considering passthrough of total TFP shocks, we have $x_{jt} = \Delta\nu_{jt}$ in the first stage, while when considering passthrough of persistent vs. transitory shocks η_{jt} and ϵ_{jt}, we include both in the first stage.

[19] It is possible that a change in marital status or spousal labor market outcomes may affect a worker's labor supply decision, leading them to switch into part-time work with lower wages. We control for this by restricting our second-stage sample to full-time workers who stay within a given firm between the two

these worker-level variables do not affect the slope of the firm-level labor supply curve, or that individual shocks do not affect the aggregate supply of labor to the firm conditional on firm characteristics. Examples of models consistent with this assumption include models of monopsonistic competition with fixed labor supply elasticities as in Lamadon et al. (2022) and Card et al. (2018), or any situation where workers are treated as atomistic by firms, as in Berger et al. (2022) and Chan et al. (2024).[20]

Mobility Estimation Results. Appendix Table B.2 shows the results from estimating Equation (4) for $\Delta\nu_{jt}$ and the productivity shocks, η_{jt} and ϵ_{jt}. Intuitively, we find that positive productivity shocks increase a worker's probability of staying at the firm, whereas negative shocks have the opposite (and a much larger) effect. In fact, as we show in Section 6, the probability of switching firms increases monotonically as productivity shocks shrink and become more negative.

We also find that men, older workers, and workers who have recently changed spouses are more likely to leave a firm, while being married, longer tenure, having a spouse who stays at their firm, and having a spouse who works in a firm experiencing a positive TFP shock, all increase the probability of staying. Joint Wald tests of all the marital/spousal coefficients across our different specifications consistently provide $\chi^2(14) > 6000$, $p < 0.001$, implying they are strongly relevant for the selection decision, though our baseline results are also robust to their exclusion. We further discuss worker mobility in Section 6.

3.3 Empirical Consistency

Our empirical identification strategy involves several important assumptions about worker mobility. Here we discuss why these assumptions are internally consistent. We make three key assumptions: (A) When estimating worker ability in Equation 2, identification of α_i and ψ_{jt} relies on the conditional exogeneity of worker mobility with respect to the idiosyncratic error term ξ_{ijt}. Formally, the assumption is $\mathbb{E}[\xi_{ijt}|\alpha_i, \psi_{jt}, X_{it}] = 0$, which restricts mobility based on factors such as unobserved worker-firm match effects. However, we can allow for

periods. We also control for hours and work position in the main second-stage passthrough regression.

[20]This assumption also implies that individual wages are not a function of worker-level bargaining processes with the firm. Given these assumptions, our instruments do not enter Equation (2) and this approach is consistent with the other assumptions on the production function and ability estimation procedures.

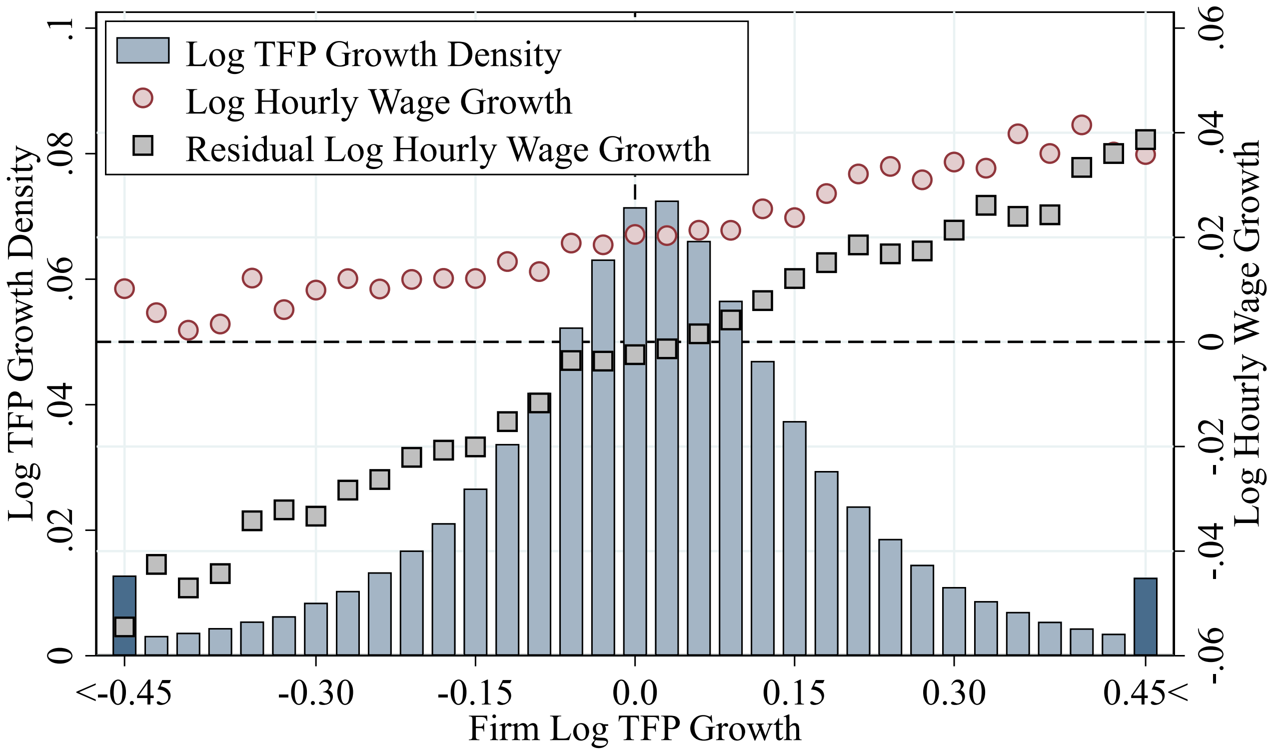
workers to choose firms based on the worker effect (α_i), observable worker characteristics (X_{it}), the firm-time effect (ψ_{jt}), or factors external to the wage equation. (B) To identify Equation 1, we assume that persistent firm productivity (η_{jt}) is correlated with the firm's labor input, but transitory productivity (ϵ_{jt}) is not. (C) To identify Equation 4, and thus the passthrough elasticity in Equation 3, we assume that workers may endogenously choose to leave firms as a function of worker characteristics (X_{it} along with marital status indicators and spousal characteristics) and firm characteristics (including η_{jt} and ϵ_{jt}).

One potential concern is that the conditional exogeneity of worker mobility in assumption A may be at odds with the endogenous mobility assumption (C). As stated, identification of Equation 2 only restricts mobility related to ξ_{ijt}. Since firm characteristics, including productivity, are embedded in ψ_{jt}, and we use the same set of worker observables throughout (X_{it}), then these assumptions are consistent as long as marital status (T_{it}) and spousal characteristics (N_{it}) do not enter ξ_{ijt} (i.e., as long as wages within a given firm do not vary with the employment status of the workers' spouses conditional on X_{it} and α_i).

A second potential concern is whether the orthogonality of ϵ_{jt} to L_{jt} (assumption B) is inconsistent with workers moving jobs in response to ϵ_{jt} (assumption C). First note that ϵ_{jt} is identified as the residual term from (essentially) an OLS regression of output on inputs, including L_{jt}, and so the estimated ϵ_{jt} satisfies assumption B mechanically. While individual labor mobility may be related to a firm's effective total quantity of labor employed, the amount of labor a firm employs is a function of total employees, total hours worked per employee, and total worker ability. As such, there are a number of possible reasons why workers may idiosyncratically respond to ϵ_{jt} even though firm-level aggregate L_{jt} does not.[21] Since we are not proposing or relying on any particular theory of wage setting, we do not take a stand on this. Ultimately, we can allow the data to tell us whether or not worker mobility is correlated with ϵ_{jt}. Our results indicate that mobility is primarily driven by η_{jt} (see Table B.2 in the Appendix), though ϵ_{jt} does play a role.

[21]For example, a firm may set a total amount of labor input necessary for a particular period in response to persistent productivity ω_{jt}. If workers quit in response to ϵ_{jt}, the firm may replace the workers, or adjust along the hours or ability margins to maintain their target labor input for the period.

Figure 1 – Passthrough from Firms' Productivity Growth to Workers' Wages



Note: Figure 1 is based on a pooled sample of firms and workers from 1996 to 2010. The blue bars show the share of firms within different bins of the log TFP growth distribution (left y-axis) for a total sample of 6.5 million worker-year and 0.57 million firm-year observations. To construct the plot, we separate firms into 41 equally spaced bins between -0.45 and 0.45. To avoid the disclosure of any sensitive information, the left- and rightmost bins, marked in darker blue, encompass the remaining left and right tails of the distribution. The red circles show the average log hourly wage growth for all workers employed by firms within a bin (right y-axis). The black squares show the average hourly wage growth after controlling for worker characteristics, firm characteristics, and endogenous selection as explained in Section 3.2 (right y-axis).

4 The Passthrough from Productivity Shocks to Wages

In this section, we discuss our main empirical results relating the changes in workers' hourly wages to different measures of firm-level productivity shocks. Before we dive into our empirical results, however, it is useful to provide a simple illustration of our main findings. Figure 1 shows the relation between log firm productivity growth and log hourly wage growth for workers. To construct this figure, we partition our sample of firms into equally sized bins based on their productivity growth between periods t and $t-1$, and plot the corresponding density on the left axis. Then, within each bin, we calculate two measures of wage growth for stayers: the average change in log hourly wages and the average residual change in log hourly wages after we have controlled for workers' endogenous mobility decisions.

Two aspects of the figure are worth noticing. First, log hourly wage growth (red circles measured on the right y-axis) is positively correlated with firm-level productivity growth (x-axis), and there seems to be downward wage rigidity. On average, wages are insulated from negative changes even for workers in firms experiencing large negative changes in productivity. In fact, average hourly wage growth is positive across the entire TFP growth distribution (all of the red circles are above zero).

Second, when we control for workers' endogenous mobility decisions, we find a significant increase in the slope between wage growth and TFP growth (black squares), which is mostly driven by a downward shift in the (residual) wage growth among workers in firms receiving negative productivity shocks. Quantitatively, not controlling for selection would lead one to conclude that for workers in firms experiencing a 30% decline in productivity, the average wage growth is roughly 1%, whereas in firms experiencing an increase in productivity of 30%, workers receive an increase in wages of 3.8%. Controlling for selection changes these numbers significantly, to negative 3.5% and to a positive 2.1%, respectively. We show in Appendix Figure B.1 that this is true for the entire wage distribution.[22] We thus conclude that controlling for endogenous mobility generates a substantial increase in the estimated passthrough of workers' wages with respect to fluctuations in firm productivity.

Baseline Regression Results

Our main passthrough estimates are based on a series of worker-level panel regressions that relate the change in workers' hourly wages to firms' idiosyncratic productivity shocks. More precisely, our baseline specification is based on Equation (3),

$$\Delta \hat{w}_{ijt} = \beta_0 + \beta^{\nu} \Delta \nu_{jt} + Z_{jt}\Gamma + X_{it}\Omega + \rho \hat{\lambda}_{ijt} + \delta_t + \zeta_{ijt}, \tag{5}$$

where $\Delta \nu_{jt}$ is the change in log TFP for firm j between periods t and $t-1$. We also include the inverse Mills ratio, $\hat{\lambda}_{ijt}$, obtained from the following first-stage regression based

[22] As we show in Figure B.1, not controlling for selection would lead one to conclude that for workers in firms experiencing a 30% decline in productivity, the median of the wage growth distribution is roughly 0, whereas the 90th percentile experienced a 6% increase in wages. After controlling for selection, the median worker in those firms instead experienced a 2.5% decline in hourly wages, whereas workers in the 90th percentile experienced an increase in hourly wages of only 3%.

on Equation (4),

$$\Pr(S_{ijt}=1)=\Phi\left(\beta_p^s\Delta\nu_{jt}+\beta_n^s\Delta\nu_{jt}\times\mathbb{I}_{\Delta\nu_{jt}<0}+X_{it}\Omega^s+Z_{jt}\Gamma^s+T_{it}\Omega_m^s+E_{it}\times M_{it}\Psi^s\right). \quad (6)$$

Table I displays our main results. Column (1) shows that there is positive and significant passthrough from firms' TFP changes to hourly wages. Quantitatively, an elasticity of 0.076 implies that a worker employed in a firm that experiences an increase in productivity of one standard deviation (about 0.24 log points in our sample) receives an increase in average hourly wages of 0.018 log points. This change amounts to $1,075 (in 2010 US dollars) for the average full-time worker in Denmark (see the bottom panel of Table I) or about 1.8% of the average annual income.[23] Given that in a typical year, around 20% of the firms in our sample (employing 25% of all private sector workers in Denmark) experience a change in productivity of at least one standard deviation from the mean, we conclude that idiosyncratic shocks to firm productivity represent an important source of earnings fluctuations.

We then analyze the passthrough of positive and negative productivity changes to wages separately using the following specification,

$$\Delta\hat{w}_{ijt}=\beta_0+\beta_p^\nu\Delta\nu_{jt}+\beta_n^\nu\Delta\nu_{jt}\times\mathbb{I}_{\Delta\nu_{jt}<0}+Z_{jt}\Gamma+X_{it}\Omega+\rho\hat{\lambda}_{ijt}+\delta_t+\zeta_{ijt}, \quad (7)$$

where β_p^ν measures the average passthrough from a positive change in ν_{jt}, whereas $\beta_p^\nu+\beta_n^\nu$ is the average passthrough from a negative change in ν_{jt}. The results are shown in column (2) of Table I. First, notice that the coefficient for a positive change is smaller than the average elasticity displayed in column (1), but still statistically and economically significant. Second, and more importantly, the elasticity of wages to a negative change in productivity is significantly larger, at 0.11.[24] This indicates that a one standard deviation change in

[23] For this calculation, we take the product of β^ν, the standard deviation of firm productivity growth, the average hourly wage of the workers in the corresponding sample, and the mean annual hours worked by full-time employees in Denmark. The result is an annualized wage effect and does not include the effect of productivity shocks on hours worked. We separately report the passthrough of productivity shocks to annual wages and hours worked in Table B.4.

[24] Juhn et al. (2018) also analyze the asymmetry of passthrough using data for the United States. They find little difference in the passthrough from positive and negative firms' revenue shocks to workers' annual earnings (Figure 4 in their paper). The main difference between our results and theirs comes from controlling for workers' endogenous mobility. In fact, column (6) in Table I shows that not controlling for mobility flips the sign of the asymmetry, in that positive shocks have a larger impact on workers' wages than negative

TFP, conditional on this change being negative, generates a decrease in annual wages for the average Danish worker of $1,600, which is roughly twice the change in wages resulting from a positive productivity shock of the same magnitude. In other words, the passthrough from firms' shocks to wages is not only significant, but also asymmetric, with negative changes in firms' idiosyncratic productivity generating much larger declines in wages than positive changes in productivity. We refer to this as "negative asymmetric" passthrough. This negative asymmetry in passthrough is consistent with, e.g., the predictions of the simple model described in Appendix E where firms have market power and operate with nearly constant returns to scale.

These findings reinforce the importance of the institutional context discussed earlier: Denmark's labor market is characterized by relatively flexible wage setting and high levels of worker mobility. The significant wage responses we observe following firm-level productivity shocks suggest that firms adjust real wages downward in response to negative shocks, consistent with the ability to negotiate flexible contracts.[25] This dynamic pattern of wage setting and worker reallocation is likely amplified by the high degree of labor market fluidity in Denmark. We further discuss the determinants and outcomes of endogenous worker job mobility and wage changes in Section 6.

Persistent and Transitory Shocks

We now turn to analyzing the impact of persistent and transitory shocks to productivity on wages. These two types of shocks can have a distinct impact on workers, as firms might be more likely to insure workers from variations in productivity that are perceived as transitory—e.g., a decline in sales because of unexpected bad weather—than from variations that are perceived as persistent—e.g., an increase in sales due to the implementation of a new online platform. Following the estimation approach introduced by Guiso et al. (2005), most papers have consistently found that persistent shocks to firms have a significant impact on wages, whereas transitory shocks do not have a significant effect on wages (see Card et

shocks (compare 0.062 versus 0.030, the sum of 0.062 and -0.032).

[25] Note that we use real wages. About 23% of workers who received a real wage cut did not receive a nominal wage cut, while the other 77% did (with a median real wage cut of 8.4%). While much of the margin of adjustment is likely on flexible pay such as bonuses, even nominal wage cuts to base pay are not rare in Denmark (see Bertheau et al. (2022)).

TABLE I – THE PASSTHROUGH FROM FIRM TFP SHOCKS TO WAGES IS POSITIVE AND ASYMMETRIC

	Change in Log Hourly Wages, $\Delta\hat{w}_{ijt}$										
	Selection Corrected				Uncorrected				Expansion	Recession	Switchers
	(1) All	(2) Pos/Neg	(3) All	(4) Pos/Neg	(5) All	(6) Pos/Neg	(7) All	(8) Pos/Neg	(9)	(10)	(11)
$\Delta\nu_{jt}$	.076	.060			.046	.062					
	(.004)	(.004)			(.003)	(.004)					
$\Delta\nu_{jt} < 0$		.053				−.032					
		(.005)				(.005)					
η_{jt}			.082	.065			.033	.044	.066	.028	.024
			(.007)	(.004)			(.004)	(.004)	(.004)	(.032)	(.007)
$\eta_{jt} < 0$				.076				−.022	.080	.131	.002
				(.007)				(.009)	(.007)	(.040)	(.002)
ϵ_{jt}			.043	.040			.034	.032	.049	.066	.057
			(.003)	(.005)			(.003)	(.004)	(.006)	(.009)	(.010)
$\epsilon_{jt} < 0$				.015				.007	.019	.004	−.018
				(.008)				(.009)	(.008)	(.016)	(.018)
$\hat{\lambda}_{ijt}$	−.219	−.278	−.202	−.283					−.230	−.333	−.012
	(.014)	(.015)	(.025)	(.013)					(.020)	(.035)	(.003)
R^2	.78	.78	.79	.79	.78	.78	.78	.78	.81	.44	.71
Obs. (000)	6,476				6,476				4,200	1,100	550
Monetary Value of a Shock to Firm TFP (US$ 2010)											
$\Delta\nu_{jt}$	$1,075				$655						
$\Delta\nu_{jt} > 0$		$840				$873					
$\Delta\nu_{jt} < 0$		$1,579				$403					
η_{jt}			$957				$386				
$\eta_{jt} > 0$				$756				$504	$756	$336	$2,065
$\eta_{jt} < 0$				$1,612				$252	$1,645	$1,897	$1,880
ϵ_{jt}			$537				$353				
$\epsilon_{jt} > 0$				$403				$319	$504	$688	$554
$\epsilon_{jt} < 0$				$554				$386	$671	$739	$369

Table I shows a set of OLS panel regressions controlling for firm and worker characteristics. All regressions include firm-level controls (i.e., firm age, lagged firm TFP level, lagged firm employment (measured by total number of hours), and lagged firm ability-adjusted labor input (L_{jt-1})), worker-level controls (i.e., a polynomial in age, lagged worker experience, lagged log wage level, lagged tenure in the firm, gender, and lagged log ability), the inverse Mills ratio to control for selection, and year fixed effects. All monetary values are in 2010 US dollars. Robust standard errors in parentheses are clustered at the firm level.

al. (2018) and Guiso and Pistaferri (2020) for recent reviews). Here, we reevaluate the role of persistent and transitory shocks by including in our baseline specification the persistent and transitory components of firm productivity estimated in Section 3.1. We estimate

$$\Delta \hat{w}_{ijt} = \beta_0 + \beta^{\eta}\eta_{jt} + \beta^{\epsilon}\epsilon_{jt} + Z_{jt}\Gamma + X_{it}\Omega + \rho\hat{\lambda}_{ijt} + \delta_t + \zeta_{ijt}, \tag{8}$$

where β^{η} and β^{ϵ} are the elasticities of wages with respect to the persistent and transitory components of firms' TFP, respectively.[26] Column (3) of Table I shows the results. We find that although transitory and persistent shocks both have a significant impact on hourly wages, wages are roughly twice as responsive to persistent (elasticity of 0.082) than to transitory productivity shocks (elasticity of 0.043).

We then separate the impact of transitory and persistent shocks into their positive and negative parts, as we do for TFP growth in Equation (7). We find a marked asymmetry between positive and negative shocks. In fact, as column (4) shows, the elasticity of wages to a negative persistent shock is twice as large as the elasticity to a positive persistent shock. In terms of annual earnings (bottom panel of Table I), a decline in η_{jt} of one standard deviation generates a decline in workers' annual labor earnings of \$1,612, whereas an increase in η_{jt} of the same magnitude generates an increase of \$756. Similarly, we find a negative asymmetric pattern for transitory shocks, with negative transitory shocks having a larger impact on wages than positive transitory shocks, although the magnitudes are much smaller than for persistent shocks.[27] This asymmetry is even starker for annual income and hours worked (Appendix Table B.4): passthrough from negative shocks to annual income is five times larger than from positive shocks. Passthrough to annual income exceeds passthrough to hourly wages only because hours worked fall sharply after negative productivity shocks; hours do not respond to positive shocks.

[26] We estimate a separate first-stage probit model for every regression specification in this paper, depending on the firm shocks and the sample in question. In this case, we obtain $\hat{\lambda}_{ijt}$ by estimating

$$\Pr(S_{ijt} = 1) = \Phi\left(\beta^s_p\eta_{jt} + \beta^s_n\eta_{jt} \times \mathbb{I}_{\eta_{jt}<0} + \beta^s\epsilon_{jt} + X_{it}\Omega^s + Z_{jt}\Gamma^s + T_{it}\Omega^s_m + E_{it} \times M_{it}\Psi^s\right). \tag{9}$$

[27] We find nearly identical results when using $\Delta\omega_{jt}$ and $\Delta\epsilon_{jt}$ instead of η_{jt} and ϵ_{jt} (see Appendix C.1).

Bias and Asymmetry

Figure 1 suggests that the bias arising from endogenous worker mobility is large, significant, and asymmetric. In our context, selection bias will affect the passthrough estimates if the probability that a worker stays at their firm (and thus remains in our baseline sample for estimating within-firm passthrough) depends on the magnitude and sign of the firm shock. Intuitively, workers in firms with larger passthrough elasticities (and thus facing larger declines in wages given a particular negative TFP shock) will be more likely to leave their firm than workers in firms with smaller passthrough elasticities. In this case, we would expect our estimates of the average passthrough for negative shocks to be biased toward zero and for the magnitude of the bias to increase with the level of passthrough. Consistent with this expectation, the estimated coefficients on the inverse Mills ratio ($\hat{\lambda}_{ijt}$) in columns (1) to (4) of Table I are negative and significant. We confirm in Appendix Table B.5 that most of the bias arises due to high-wage workers exposed to high passthrough elasticities, while selection correction does little to change the passthrough estimates for low-wage workers that typically experience low passthrough elasticities.

To evaluate the extent of the bias, we repeat the previous analysis without correcting for worker selection (i.e., we exclude $\hat{\lambda}_{ijt}$ from our regressions). The results are shown in columns (5) to (8) of Table I. As expected, we find that selection biases the estimated coefficient of firms' shocks on hourly wages toward zero. Moreover, the bias is more significant for persistent than transitory shocks. To see this, compare columns (3) and (7), where the elasticity to persistent shocks declines from 0.082 to 0.033 when we do not control for selection, but only declines from 0.043 to 0.034 for transitory shocks. Consistent with the intuition above, the passthrough estimates for negative shocks are the most affected by selection: if we ignore it, we would conclude that negative persistent shocks have a passthrough elasticity of 0.022, which is just one-sixth of our baseline (corrected) estimates. These uncorrected results would lead us to conclude that passthrough is positive asymmetric, and wages are not responsive to negative shocks to firm productivity. Given the importance of properly controlling for selection, all the results that follow include selection correction terms.[28]

[28] In Appendix C, we explore the bias that results from removing each additional step of our empirical

Persistence

We now discuss the long-term impact of firms' shocks on workers' wages. Intuitively, if shocks to firms only translate into a short-lived change in workers' wages (even when the shocks to firms are persistent), one should expect large contemporaneous passthrough (a positive and significant correlation between a TFP shock in period t and a change in workers' wages between t and $t-1$), but a smaller passthrough at longer horizons. To study the persistence of passthrough, we modify our baseline specification in Equation (8) by extending the horizon of the wage change on the left-hand side from t to $t+k$, where k can take values between 0—as in our baseline case—and 4. Importantly, we keep constant the period in which we measure firms' productivity shocks and other firm and worker observables while also controlling for the full sequence of shocks from t to $t+k$.[29]

Figure 2 shows the elasticity of workers' wages to a persistent or transitory shock to firm productivity at different horizons estimated from a separate set of first- and second-stage regressions. The left panel shows that the passthrough from persistent TFP shocks is not only statistically significant in the first year—our baseline estimate—but also persists after 4 more years, with almost no decay in magnitude. In contrast, short-lived transitory shocks—shown in the right panel—have a smaller effect on wages that rapidly dissipates.

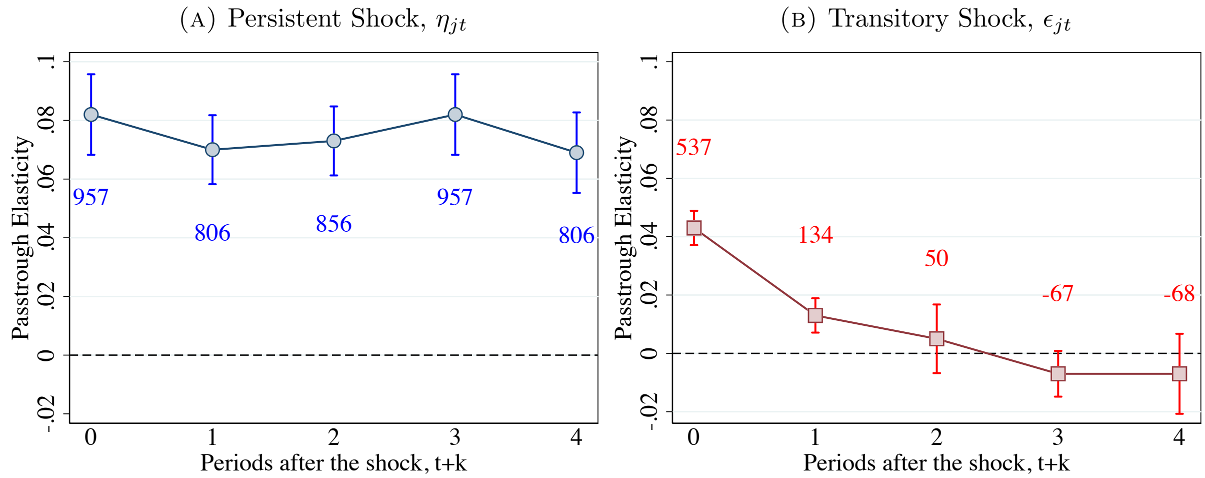
Aggregate State Dependence

Does the passthrough from idiosyncratic firm shocks to workers' wages change during recessions relative to expansions? This could occur if, for instance, a major aggregate shock such as the Great Recession reduces the value of unemployment for workers (e.g., due to fewer vacancies), thereby lowering reservation wages and allowing firms to pass on negative

approach. In particular, we show that controlling for hours worked cuts passthrough estimates in half, while controlling for worker ability and using our measure of productivity shocks significantly increases estimated passthrough. We provide intuition for what drives the magnitude and direction of selection bias using a simple model in Appendix D. In Appendix Table B.6, we show that several approaches to reweighting observations based on (lagged) firm size or the share of stayers in a firm do not substantially correct for endogenous mobility, though weighting observations by the inverse of lagged employment at a worker's firm does increase estimated passthrough as it puts more weight on small firms, which have greater passthrough, as we show in Section 5.1.

[29] To single out the effect of the t-period shock on the long-run change in wages and avoid bias due to within-firm autocorrelation of shocks, in this exercise, we control for all relevant persistent and transitory shocks for each regression. For example, to examine the passthrough of η_{jt} and ϵ_{jt} on wage changes from $t-1$ to $t+2$, we additionally control for η_{jt+1}, η_{jt+2}, and ϵ_{jt+1}, ϵ_{jt+2}.

FIGURE 2 – SHOCKS TO FIRMS HAVE A LONG-LASTING IMPACT ON WORKERS' WAGES



Note: The left panel (right panel) of Figure 2 shows the elasticity of hourly wages to a persistent (transitory) shock to firms' productivity. Each point on the graph is the coefficient from a separate regression where the dependent variable is the change in workers' hourly wages at different time-horizons (defined by $k \geq 0$). The vertical lines show 95% confidence intervals around the point estimates. In each plot, the numbers above and below the lines represent the monetary value of a shock of one standard deviation calculated using the corresponding elasticity. All monetary values (in 2010 US$) are calculated relative to the average annual labor earnings within the corresponding group.

shocks more easily. Similarly, tighter credit constraints during downturns may limit the ability of firms to protect workers against idiosyncratic shocks, increasing passthrough.

To test for state dependence, we estimate Equation (8) separately for the Great Recession and for all other (expansionary) years. The results in columns (9) and (10) of Table I show that the passthrough from positive shocks is state dependent, while the passthrough from negative shocks is not. During expansions, passthrough estimates align with our baseline (compare columns (9) and (4)), as most sample years are expansionary. In recessions, however, passthrough from persistent negative shocks remains relatively unchanged (recall it is given by $\beta^{\eta}_{p} + \beta^{\eta}_{n}$), indicating firms still reduce wages when hit by negative shocks. In contrast, passthrough from positive shocks nearly vanishes, suggesting that firms experiencing positive shocks during the recession did not pass these gains on to workers.[30]

Passthrough of Revenue vs Quantity TFP

As noted in Section 3.1, our measure of productivity is revenue productivity, or TFPR. Though we do not observe output prices and therefore cannot estimate passthrough of efficiency (TFPQ) to wages, we show in Appendix F that we can do a simple decomposition

[30] See Grigsby et al. (2021), who document a drop in the probability of wage increases and a rise in wage cuts for U.S. workers during the Great Recession.

of TFPR passthrough using a standard model of downward sloping output demand. The key result is that the passthrough from TFPQ to wages can be expressed as a fraction $\theta^d < 1$ of TFPR passthrough that depends on the output demand elasticity ε^d. In particular, $\theta^d = (\varepsilon^d - 1)/\varepsilon^d$ is equal to the inverse markup. Standard estimates of markups range from 1.10 to 1.30 (see De Loecker and Warzynski (2012) and Edmond et al. (2015)), which implies that passthrough from TFPQ in our setting is between 0.059 and 0.070, while passthrough from demand shocks ranges from 0.007 to 0.018.

5 Heterogeneous Passthrough

As we have shown, the average passthrough from firm shocks to wages is significant and asymmetric. However, it is possible that the overall effect masks substantial heterogeneity across firm and worker types. For example, firms with different labor market power, productivity, or size may pass shocks to their workers at different rates, which we analyze in Section 5.1. Then, in Section 5.2, we study whether workers of different ability, age, or tenure are subject to different passthrough. The main conclusion of this section is that the passthrough from firm shocks to wages is highly heterogeneous and varies substantially across firm and worker groups. To conserve space, in this section we focus on the passthrough from persistent shocks, and we present equivalent results for the impact of transitory shocks in Appendix B.

5.1 Firm Heterogeneity

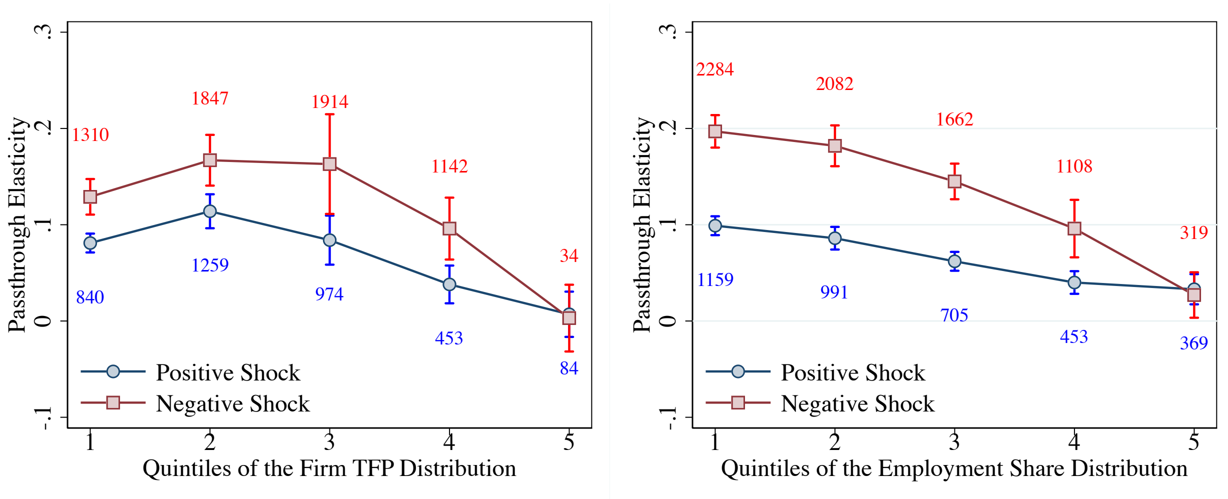
Firm Productivity. We first study whether firms with different productivity levels differ in their level of passthrough. This would be the case if firms differ in the degree to which they face financial or labor adjustment constraints, or have some degree of labor market power such that high-productivity firms face a more inelastic labor supply. Our results are consistent with both interpretations, and indicate that the wages of workers employed by low-productivity firms are significantly more exposed to firm shocks than workers employed by high-productivity firms, both for positive and negative shocks.

We show this by separating our sample of workers into quintiles of their firm's (lagged) log TFP level, ν_{jt-1}. We then run our baseline specification (Equation (5)) separately within

Figure 3 – Passthrough is Heterogeneous across Firm Characteristics

(a) Firm TFP

(b) Firm Employment Share



Note: Figure 3 shows the elasticity of hourly wages across different workers employed in firms with different characteristics. Panel A shows the passthrough within quintiles of the (lagged) TFP distribution; Panel B shows the passthrough within quintiles of the labor market employment share of a firm, where the labor market is defined as by a 2-digit NACE/Municipality bin. The vertical lines show 95% confidence intervals around those point estimates. In each plot, the numbers above and below the lines represent the monetary value of a shock of one standard deviation, calculated using the corresponding elasticity. All monetary values (in 2010 US$) are calculated relative to the average annual labor earnings within the corresponding group. All regressions include the same worker and firm controls as our baseline regressions in Table I.

each group. Figure 3a shows the results. We find that the passthrough from persistent shocks to firms (both negative and positive) is decreasing in firm productivity, especially in the top three quintiles of the distribution. For example, workers employed at firms in the lowest productivity quintile gain \$840, or 1.6% in annual income on average when their firm experiences a positive persistent shock of one standard deviation. The impact of negative shocks is even larger, with a \$1,310 drop in annual earnings—or 2.6% of average earnings—after a negative productivity shock. Workers employed at firms in the highest quintile of the TFP distribution, in contrast, experience much smaller wage changes. On average, these workers gain \$84, or 0.1% in annual income (lose \$34, or 0.05% in annual income) when their firm receives a persistent positive (negative) shock of one standard deviation. This heterogeneity is consistent with models in which productive firms are large and less financially constrained—which is the case in our sample—and thus better equipped to absorb negative shocks, a la Michelacci and Quadrini (2009) where financially constrained firms borrow from their workers at the beginning of the firm life cycle.[31]

[31] We find a strong negative correlation between firm TFP and debt-to-asset ratios in our data, conditional on firm age.

Firm Size and Market Power. Passthrough might also vary across firms within labor markets due to differences in labor market power. Firms with greater labor market power will tend to have larger labor market shares (conditional on productivity) and be situated on more inelastic portions of their labor supply curve. We investigate this in Figure 3b where we partition our firm sample into quintiles based on their employment share within an industry-municipality bin.[32]

Consistent with models of monopsonistic competition in the labor market (for example, Berger et al. (2022)), the passthrough from positive and negative shocks is declining in labor market share. Quantitatively, workers employed in firms in the first quintile of the employment share distribution—i.e., small firms with around 0.6% of employment in their local labor market—gain $1,159 from a one standard deviation increase in persistent productivity, and lose $2,284 after a negative shock of the same magnitude. In contrast, workers employed by firms in the fifth quintile—large firms with around 10% of employment in their local labor market—are better insured, experiencing gains (losses) of $369 ($319) from positive (negative) persistent shocks of one standard deviation. This heterogeneity is consistent with the predictions of our simple model of market power and oligopsonistic competition, which links differences in passthrough directly to the firm's market share.[33]

5.2 Worker Heterogeneity

Wages and Ability. A long-standing literature has indicated that workers are paid in part for their performance (e.g., Paul and Scott (2011)), hence tying their compensation to the outcomes of the firm (Kruse et al., 2012; Franceschelli et al., 2010; Lazear, 2000). This is even more clear for executives and top managers who are at the top of the earnings distribution (Gabaix et al., 2014). Hence, one would expect that the passthrough from

[32]We calculate employment shares within each industry-municipality bin, where an industry is defined at the 2-digit industry level. This is a fairly granular definition of a labor market, with the median firm within the top employment share quintile having around a 10% share of employment within that market. For confidentiality, we calculate the median share within a quintile as the average share for all firms between the 50th and 51st percentiles of the employment share distribution within each quintile. Quintiles 1 through 4 have a within-quintile median labor market shares of 0.6%, 1.4%, 4.7%, and 6%, respectively.

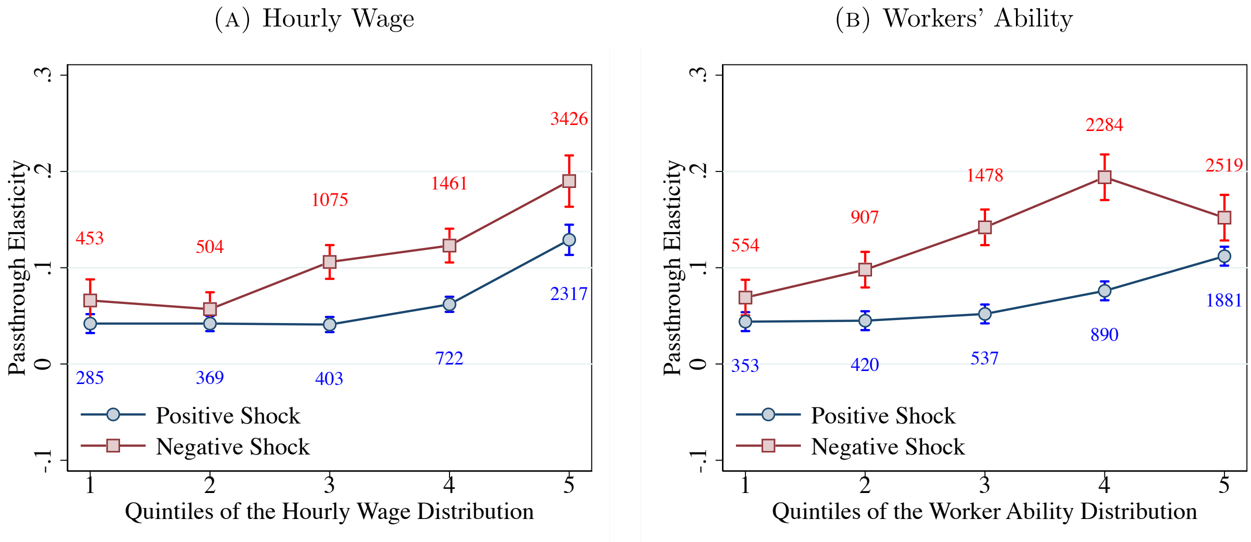
[33]We find a similar negative relation between passthrough and firm size, as measured by the number of workers. As shown in Figure B.3, the passthrough elasticity declines from above 0.1 for firms of fewer than 5 workers to approximately 0 for firms with 500 workers or more. This indicates that large firms are quite effective at insulating their workers from idiosyncratic firm-level risk.

firm shocks to wages increases as we move from low- to high-earnings individuals. To see whether this is the case, we separate workers into quintiles based on their past hourly wage and estimate the passthrough from persistent and transitory shocks within each quintile. Figure 4a summarizes our results. The differences in passthrough between low- and high-wage workers after a persistent shock to firm productivity are substantial: the elasticity to positive shocks for workers in the fifth quintile of the distribution is more than twice as large as the elasticity for workers in the first quintile (a β^{η} of 0.04 versus 0.1, respectively). Quantitatively, we find that workers at the fifth quintile of the distribution gain six times more in annual income than workers at the bottom quintile ($2,317 versus $285, or 2.5% and 0.8% of the within-group average annual income, respectively) when their firms receive a persistent positive shock to firm TFP of one standard deviation. This difference is even starker for negative shocks. Workers in the top wage quintile lose $3,426 in annual labor earnings after such a shock, while those in the bottom quintile lose only $453.

We find a similar pattern when we look at worker "ability", as measured by the sum of a worker's fixed effect and time-varying observable characteristics, $\hat{\alpha}_i + X_{it}\hat{\Gamma}_t$. Figure 4b shows these results. Similarly to the hourly wage, workers at the bottom of the ability distribution are much less exposed to firm shocks than those at the top of the distribution. In other words, high-ability workers experience larger gains and losses than low-ability workers when their firms experience persistent TFP shocks. This is consistent with the notion that labor earnings for high-income workers such as managers are more linked to firm performance than for low-income workers.[34] Note that these results on worker heterogeneity should be interpreted with our estimation assumptions in mind. We assume that all workers within a firm receive the same hourly wage (per unit of ability), so observed differences across workers reflect their allocation to firms with different passthrough rates rather than within-firm variation in passthrough.

[34]Consistent with our baseline estimates, the quantitative effect of transitory shocks to TFP is considerably smaller than the effect of persistent shocks. As shown in Panel A of Appendix Figure B.2, the quantitative impact is larger for workers in the fifth quintile than for those in the first (e.g., $1,696 to $319 in the case of a negative shock). These differences are mainly driven by differences in the annual earnings of each group rather than by the responsiveness of hourly wages to firm shocks.

Figure 4 – Passthrough is Heterogeneous Across Worker Characteristics



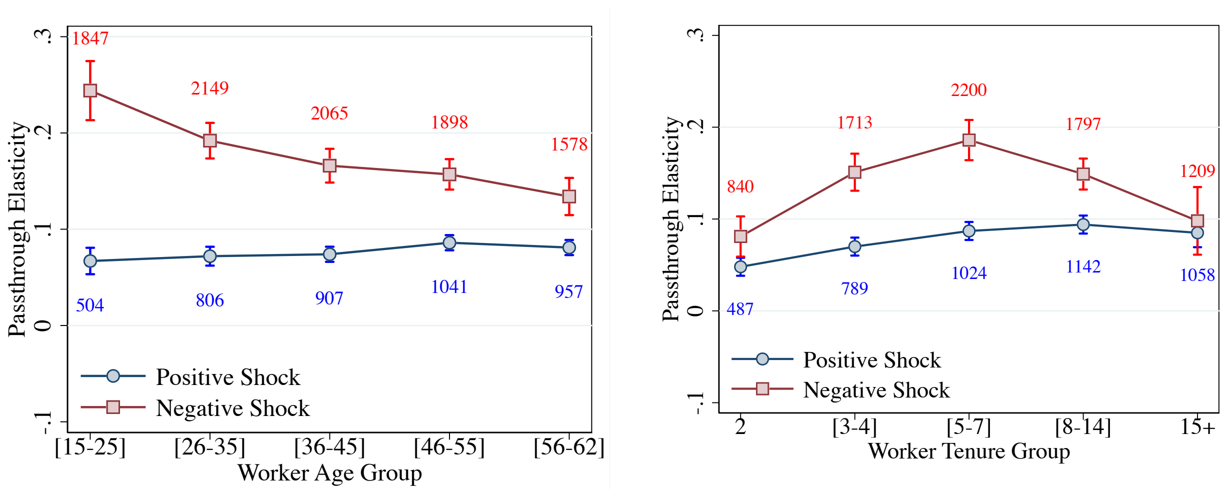
Note: Figure 4 shows the elasticity of hourly wages across different workers' characteristics. Panel A shows the passthrough within quintiles of the hourly wage distribution. Panel B presents similar statistics for workers in different quantiles of the ability distribution as measured by $\exp(\hat{\alpha}_i + X_{it}\hat{\Gamma}_t)$. The vertical lines show 95% confidence intervals around those point estimates. In each plot, the numbers above and below the lines represent the monetary value of a shock of one standard deviation, calculated using the corresponding elasticity. All monetary values (in 2010 US$) are calculated relative to the average annual labor earnings within the corresponding group. All regressions include the same worker and firm controls as our baseline regressions in Table I.

Tenure and Age. Workers may be more or less exposed to firm shocks, depending on their age and tenure within the firm. For instance, older workers are more likely to have accumulated general work experience, have differing tenure-contingent contracts, or have accumulated specific human capital that is valuable for the firm and difficult to replace. In such cases, the firm may try to insure an older and long-tenure workforce from negative shocks more than a younger or recently-hired workforce. Alternatively, workers with longer tenure might receive a higher increase in earnings after a positive productivity shock, relative to a younger worker, if the firm implicitly "borrowed" from them. Our results are consistent with this intuition.

Figure 5a shows the elasticity of wages to a persistent shock to firm productivity for workers in different age groups. Three features of the figure are worth noticing. First, the passthrough from persistent positive shocks is weakly increasing with worker age. This implies that older workers get a higher wage increase than younger workers when firms receive a positive TFP shock, although the difference is not large. In contrast, the response of wages to a negative persistent TFP shock is larger than the response to positive shocks

Figure 5 – Passthrough is Heterogeneous Across Worker Characteristics

(a) Worker Age (b) Worker Tenure



Note: Figure 5 shows the elasticity of hourly wages across different workers' characteristics. Panels A and B present statistics for workers in different groups of the age distribution and the tenure distribution, respectively. We choose the tenure cutoffs so as to have groups of roughly similar size. The vertical lines show 95% confidence intervals around those point estimates. In each plot, the numbers above and below the lines represent the monetary value of a shock of one standard deviation calculated using the corresponding elasticity. All monetary values (in 2010 US$) are calculated relative to the average annual labor earnings within the corresponding group. Regressions include the same controls as our baseline regressions in Table I.

and decreases monotonically with age. For instance, workers who are 56 years old or more lose 2.6% of their annual income in response to a one standard deviation negative shock, whereas workers who are between 15 and 25 years old lose 3.9% of their annual income on average.[35]

We then divide our sample of workers into five tenure groups: workers with a tenure equal to 2 years or less, a tenure between 3 and 4 years, between 5 and 7 years, between 8 and 14 years, and 15 years or more. Then, we run our baseline regression specification within each group controlling for worker tenure in the firm. The results are shown in Figure 5b. We find that the passthrough from persistent TFP shocks to wages is hump-shaped in tenure. In fact, the effect of negative shocks is almost the same for newly hired workers as for workers who have been in the firm for more than 15 years. Workers in the middle of the tenure distribution, instead, appear to be much more exposed to negative firm shocks than

[35] In contrast, we find that young workers gain more from a positive transitory shock and lose less after a negative shock than older workers (see Panel C of Appendix Figure B.2). More precisely, for workers who are 25 years old or younger, a negative (positive) transitory shock of one standard deviation translates into a decrease (increase) of $605 ($470) in annual earnings. For workers who are 56 years old or older, a negative (positive) shock of the same magnitude generates a decrease (increase) of $873 ($521) in annual earnings.

the rest of the workers: when the shocks are negative, workers with medium tenure (between 5 and 7 years) lose the most, with a negative shock of one standard deviation generating a decline of $2,200 (3.5%) in their average annual income.

The decline in passthrough as individuals age is consistent with the predictions of a model where there is double-sided lack of commitment between workers and firms such as in Souchier (2023). In such a model, if older workers decrease their search intensity, the passthrough will decline. In the limit, if workers stop searching for new jobs, there is full commitment from the side of the worker, pushing the effective passthrough to 0. Combining such a model with one where workers accumulate firm-specific human capital could help to rationalize the hump-shaped profile of passthrough over tenure.

6 Switchers

The previous sections focused on the effect of TFP shocks on stayers. However, roughly 20% of workers in our sample switch firms in any given year, potentially in response to changes in firm productivity. We now turn to these "switchers", defined as workers who change their primary employer between two consecutive years. Studying the response of switchers is important since our selection correction approach is based on the idea that workers move in response to firm-level productivity shocks.

Firm productivity shocks can affect switchers through several channels. First, as discussed in Section 3.2, productivity shocks influence employment risk and job mobility. The left panel of Figure 6 shows that the probability of switching (right y-axis) increases monotonically with the magnitude of the negative productivity shock. Workers are more likely to leave firms experiencing larger declines in TFP. To quantify this relationship, we estimate separation elasticities with respect to persistent TFP shocks. Specifically, we estimate our first-stage probit model in Equation (4), but change the dependent variable to $S_{ijt} = 1$ if a worker switches firms. We then calculate the predicted probabilities of moving for each worker and report the mean separation elasticities in Table II. We find a mean separation elasticity of -1.85. As implied by Figure 6, these elasticities are highly asymmetric, with a separation elasticity of -0.72 for positive shocks and -2.39 for negative shocks, implying that

Table II – Separation Elasticities for a Persistent Productivity Shock η_{jt}

	Average	**Positive Shocks**	**Negative Shocks**
Separation Elasticity	-1.85	-0.72	-2.39

Note: Values are mean separation elasticities with respect to a persistent productivity shock η_{jt}. The elasticities are calculated as $\hat{\beta}^s \phi(\hat{Z}_{ijt})/\Phi(\hat{Z}_{ijt})$ where $\hat{\beta}^s$ is the coefficient on η_{jt} and $\hat{Z}_{ijt}$ is the predicted value from a probit regression of a switching indicator on individual and firm characteristics as in Equation (4).

a 1% decrease in persistent productivity increases the probability of separating by 2.39%.[36]

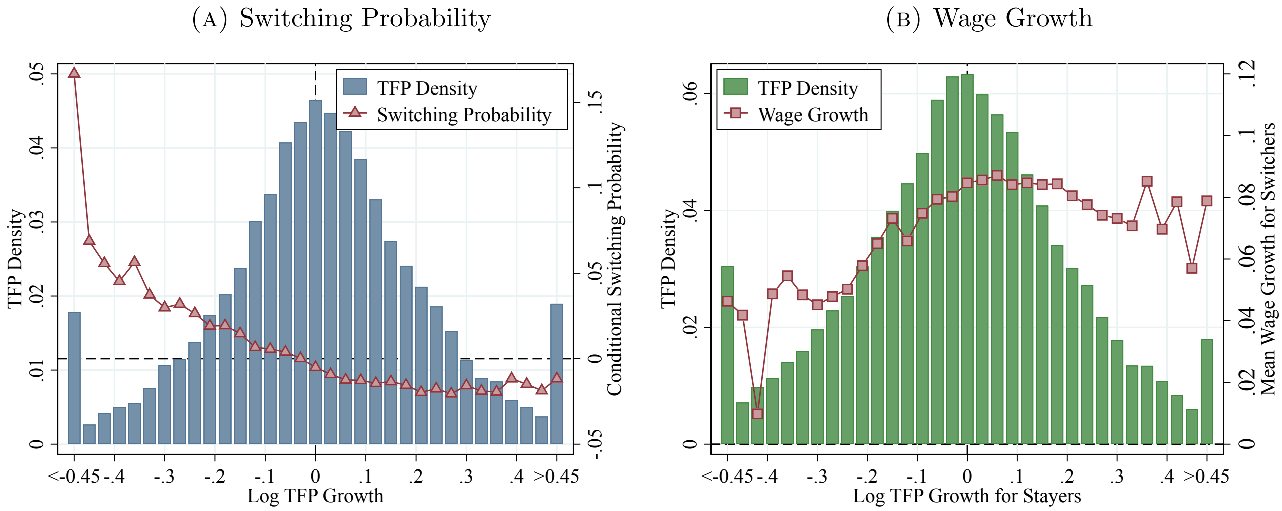
Are workers leaving shrinking firms voluntarily, or are they being displaced? This distinction matters, as displaced workers typically suffer wage losses, while voluntary movers are more likely to avoid wage cuts or even receive higher wages. To shed light on this, we examine average wage growth for switchers across the distribution of their origin firms' productivity. The right panel of Figure 6 shows that average wage growth is positive across the entire distribution. Workers tend to earn more at their new firm regardless of whether their previous firm experienced a productivity increase or a decline, suggesting that these separations are primarily voluntary rather than representing layoffs. In Appendix Figure B.4, we further explore how the share of switchers, the switching probability, and the (lagged) wage of switchers differ along the distribution of residualized TFP changes.[37] Consistent with Figure 6, larger negative shocks induce a higher probability of (and thus a higher share of workers) switching out of the firm. As shocks become more negative, it is more likely that those who switch firms are high-wage workers who typically experience higher passthrough (Figure 4). In contrast, the probability of switching due to positive shocks is uncorrelated with the worker's wage.

Interestingly, while switchers with wage losses tend to move to firms with similar productivity levels (Appendix Figure B.5a), these destination firms are on average still growing and experiencing positive productivity shocks (Appendix Figure B.5b). This pattern supports the view that many workers switch proactively in response to negative shocks at their origin firms, reinforcing the importance of accounting for endogenous mobility when estimating

[36]These results are in line with other studies that examine employment adjustments and worker mobility following firm shocks, e.g., Carlsson et al. (2021) and Maibom and Vejlin (2021).

[37]We obtain residualized TFP changes by regressing $\Delta\nu_{jt}$ on the full set of controls. We then calculate the mean switcher share, lagged switcher wage, and predicted switching probability within each bin of residualized TFP change.

Figure 6 – Switching Probability and Wage Growth for Switchers



Note: Figure 6a shows the probability (from a linear version of Equation 4) of an individual switching firms between periods $t-1$ and t conditional on the TFP change of the firm where the individual worked in period $t-1$. Figure 6b shows the average log wage growth experienced by switchers between periods $t-1$ and t after a switch ($\log W_{ijt} - \log W_{ikt-1}$) conditional on the TFP change of the firm where the individual worked in period $t-1$ (i.e., $\Delta\nu_{kt}$).

passthrough for incumbent workers.

Second, the wage change that results from this employment change may depend on the productivity level and growth of the firms that a particular worker is moving across. Therefore, to obtain quantitative estimates of the between-firm passthrough elasticity, we run a panel regression similar to the baseline model we consider in our stayer sample. To maintain consistency in interpretation across our stayer and switcher specifications, we define a worker-level productivity shock as $\nu_{j(i,t),t} - \mathbb{E}[\nu_{j(i,t-1),t}|\nu_{j(i,t-1),t-1}]$, where $j(i,t)$ denotes the firm where worker i is employed in period t and $\nu_{j(i,t),t}$ is that firm's productivity in period t. For stayers, this equals $\eta_{jt} + \epsilon_{jt}$ as in previous sections and represents an unanticipated change in productivity in the firm in which they work (i.e.: $\eta_{jt} = \omega_{jt} - \mathbb{E}[\omega_{jt}|\omega_{jt-1}]$). For a switcher moving from k to j, this equals $\eta_{jkt}+\epsilon_{jt}$, where $\eta_{jkt} \equiv \omega_{jt} - \mathbb{E}[\omega_{kt}|\omega_{kt-1}]$, representing the unanticipated difference in productivity between the two firms. Hence, a positive TFP change for a switcher implies that the worker moved to a firm with higher realized TFP relative to the expected TFP of the firm at which they used to work.

To estimate the passthrough elasticity for switchers, we modify our baseline specification to include η_{jkt} plus observables for both firms. In particular, we estimate

$$\Delta\hat{w}_{ijkt} = \beta_0 + \beta_p^\eta \eta_{jkt} + \beta_n^\eta \eta_{jkt} \times \mathbb{I}_{\eta_{jkt}<0} + \beta_p^\varepsilon \epsilon_{jt} + \beta_n^\varepsilon \epsilon_{jt} \times \mathbb{I}_{\epsilon_{jt}<0} + Z_{jt}\Gamma_1 + Z_{kt}\Gamma_2 + X_{it}\Omega + \rho\hat{\lambda}_{ijt} + \delta_t + \zeta_{ijkt},$$

where $\Delta\hat{w}_{ijkt}$ is the change in the ability-adjusted real log hourly wages of an individual who moved from firm k to firm j and ϵ_{jt} is the transitory shock at the new firm. The matrices Z_{jt} and Z_{kt} include firm j's and k's characteristics such as size, age, and lagged productivity.[38]

Column (11) of Table I shows the results of this analysis. Notice that the elasticity of switchers' wages to firms' TFP shocks is smaller than for stayers (compare to column (4) in Table I), but the dollar value of the shock is much larger for switchers (bottom panel of Table I). The large difference in the dollar values between switchers and stayers stems from the differences in the dispersion of TFP changes, as well as differences in the average wage. For example, the elasticity of wage growth to a persistent negative TFP shock is much larger for stayers than for switchers (0.141 versus 0.026).[39] However, the average wage loss from a one standard deviation within-firm negative TFP shock is smaller than the loss from a persistent one standard deviation firm-to-firm drop in TFP (compare \$1,612 versus \$1,880, or 2.7% versus 3.3% of average annual income). One additional remarkable difference with respect to stayers is that the passthrough for switchers is symmetric (the coefficient on $\eta_{jkt} \times \mathbb{I}_{\eta_{jkt}<0}$ is effectively 0). This implies that workers climbing up the productivity ladder face similar wage changes as those making equal movements down the ladder, and that the asymmetry in passthrough for stayers is driven by the firm.

7 Conclusion

In this paper, we present new evidence on the passthrough from firms' productivity shocks to workers' wages. The passthrough elasticity—defined as the percentage variation in hourly

[38]Note that $\eta_{jkt} = \omega_{jt} - \mathbb{E}[\omega_{kt}|\omega_{kt-1}] = \eta_{jt} + \mathbb{E}[\omega_{jt}|\omega_{jt-1}] - \mathbb{E}[\omega_{kt}|\omega_{kt-1}]$. This conceptually implies that our measure of cross-firm productivity passthrough may include the effect of source-firm TFP levels on destination firm wages, which could be rationalized using theoretical frameworks such as Postel-Vinay and Robin (2002). Since, much like stayers, a worker's exposure to η_{jkt} is endogenous, we control for selection in this regression by including the inverse Mills ratio $\hat{\lambda}_{ijt}$, which is estimated from the first-stage model for switchers that we discussed above when calculating the separation elasticities.

[39]Recall that the elasticity of wages to a negative shock is the sum of $\beta_p + \beta_n$.

wages generated by a percentage change in firms' productivity—is positive, economically large, persistent, and asymmetric. A negative shock to firm productivity generates a much larger decline in wages, relative to the gain in wages from a positive shock to firm productivity of the same magnitude. These results rely crucially on i) controlling for workers' endogenous mobility decisions, ii) identifying exogenous firm productivity shocks, and iii) controlling for unobserved heterogeneity in worker ability. We also find substantial variation across several key dimensions of worker and firm heterogeneity. We find passthrough decreases with firm size, productivity, and labor market share, which suggests that labor market power plays an important role in wage setting.

Finally, we show that worker mobility is responsive to firm productivity shocks, and that this matters for interpreting wage dynamics. The probability that a worker switches employers is strongly negatively related to firm-level productivity shocks, with separation elasticities that are notably more elastic for negative shocks. Despite this, average wage growth for switchers is positive across the productivity distribution, suggesting that many workers switch proactively to avoid wage cuts rather than being involuntarily displaced. However, wage gains are smaller for those leaving firms hit by large negative shocks, consistent with a greater incidence of involuntary separations in such cases. These patterns underscore the importance of accounting for endogenous mobility in estimating wage passthrough, and more broadly highlight the allocative role of worker mobility in responding to firm-level shocks.

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Online Appendix for "Heterogeneous Passthrough from TFP to Wages"

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February 4, 2026

A Data and Variable Definitions

In Table A.1 at the end of this section, we show the list of worker- and firm-level variables used in our analysis. The names available here are those present in the Danish Integrated Database for Labor Market Research. Further details can be found by visiting this website (in Danish).

A.1 Data cleaning and preparation

Our estimation proceeds in several steps. The first step is estimating the two-sided fixed effect regression to obtain our measure of individual ability and firm ability price. This requires individual-level data on employer and hourly wage for each employment spell within a year. The Danish registers we use (IDAN, IDAPALL), record this information at the annual level. In particular, for each individual, we see every job spell they worked during a given calendar year, their total income from that spell (joblon), the number of days worked at that job (ansdage), information about regular hours worked and type of job (type, pstill, jobkat, tilknyt), and their hourly wage (timelon) which includes bonuses and overtime income.

For each worker, we keep the three most significant (by total income) job spells within a given year. The combination of timelon, joblon, ansdage and jobkat/tilknyt allows us to obtain a reliable continuous measure of total hours worked during a spell, which we use to create a worker-level measure of full-time equivalents (FTE) for use in our production function estimation procedure. We do this by calculating the average hours worked by "full time employees" who work at a job for an entire year (365 days), and dividing each worker's actual hours worked at each job spell by this number. We deflate our measures of total job income and hourly wage by the consumer price index provided by Statistics Denmark. Our two-sided fixed effect procedure also includes controls for individual occupation, education, work experience, sex, age, tenure and position within the firm. Occupation is a 4-digit code corresponding to the DISCO_88 standard. Education is a one-digit code (created from hfaudd) corresponding to highest educational achievement. Position within the firm (pstill, still) includes statuses such as manager, highly skilled professional, low skilled worker, etc. These variables along with sex (koen) enter as sets of indicators in the two-sided fixed effect regression, while age, experience and tenure enter as continuous variables. Here we drop workers with missing or military occupation codes. We also drop everyone whose job code is "employer", or who is not attached to a firm (this includes workers coded as "supporting spouse" or "self-employed").

The remaining sample is used for the two-sided fixed effect regression. Note that here we include up to three job spells for each worker, including part-time jobs. When we eventually run our passthrough regressions, we will only keep each worker's primary full-time position. The reason to include every job at this stage is to maximize the connected set for the two-sided fixed effect regression and to avoid biasing our productivity estimation (as dropping part-time employment spells may lead to under-counting the labor input at firms which employ part-time workers). Once we have our individual-level measures of ability, we are able to construct a firm-level measure of total ability-weighted hours of labor. We divide this measure of total ability by the total FTE supplied to the firm (the sum of individual-level FTE employed at that firm during that year). This provides a measure of ability-per-FTE for each firm and year. We will multiply this by a firm-year measure of annual FTE from the firm register to obtain the firm-level labor input.

Our firm-level data is drawn from two registers: FIRM and FIRE. We use FIRM to construct a reliable measure of firm age and start date. All of our other firm-level data comes from FIRE. In order to estimate TFP, we need measures of output (revenues), inputs (capital, labor, materials) and industry. We use two digit industry codes to deflate material expenditures, capital/investment and output using industry-level price and cost deflators. We use more aggregated industry codes when we control for industry in the production function estimation and passthrough regressions. There are 16 of these codes, corresponding to the following sectors: Agriculture, Extraction, Manufacturing, Energy, Water, Construction, Wholesale/Retail Sales, Transportation, Hospitality, ICT, Finance, Real Estate, Professional/Scientific/Technical , Administrative Services, Arts/Entertainment, and Services. We construct gross revenues by summing revenue from sales (oms), capital gains (auer), other operating income (adr) and changes in inventory (dlg). Materials is constructed generally as purchases of subcontracts and salary work (non-employees), purchase of energy, purchase of raw materials, auxiliary materials, finished goods and packaging (excluding purchase of energy), purchase of goods for resale, expense for rent, expenses for the acquisition of small equipment, operating assets with a short lifespan, secondary expenses, and other external expenses. In particular, we sum the following variables: kvv, krhe, kene, kloe, udhl, uasi, udvb, ulol, ekud, otde, seud, aneu, oeeu. Not all of these are included every year, as variable definitions change over time.

We construct the firm's total labor cost as the wagebill (lgag) plus pension costs (pudg) and other social security costs (audg). The firm's total labor input is the ability-per-FTE measure calculated from the worker data, multiplied by the measure of FTE reported by the firm in the FIRM register.[40] We construct capital using the perpetual inventory method, where our initial measure of the capital stock is the firm's tangible fixed assets at year end (maat). We calculate forward using a depreciation rate of 0.08 and net investment calculated as the value of newly acquired fixed assets less the value of fixed assets sold (atit - afat). The last variable we need is the revenue share of material expenditures, which we calculate using the nominal values of each, following GNR. This gives us everything necessary to estimate firm productivity. Our estimation sample includes all firm-year observations which do not have missing values for revenue, capital, materials, labor (which is fte $\times$ ability), lags of each, and two-period lags of labor. We also drop firms which have imputed values for any of those (as reported by the jkod variable).

Given our measures of firm productivity, we finally move on to constructing and cleaning the data for our passthrough regressions. We use data on relationship status and spousal identity to link workers to their spouses, and to create indicator variables indicating whether a worker is married, just got married, is separated, or changed their partner/spouse in a given period. We are also able to link all of the spouse's demographic information to the worker, and all of the spouse's firm's information if the spouse is employed. This allows us to construct the additional variables we use for the selection correction procedure. Here we include an indicator for whether a spouse works at the same firm as the worker and exclude that spouse's firm-level variables if so. Our final estimation sample for the passthrough regressions are restricted to workers who are 15 years or older, have an annual full-time

[40] We also perform the estimation using the firm-level FTE measure from the worker data and find essentially the same results. The two measures are very highly correlated.

List of Variables used in the Analysis

Name	Description
	Worker-Level Variables
pnr	Worker ID
erhver	Professional experience from 1980
pstill	Primary work position
aegte_nr	Spouse ID
koen	Sex
kom	Location, Municipality code
alder	Age
arbgnr	Employer number
timelon	Hourly wage in employment
lbnr	Workplace serial number identifier
type	Position type
still	Position
persbrc	Industry NACE code
jobkat	Job type in the employment
joblon	Salary amount in the employment relationship
discoalle_indk	Occupational classification (1991 to 2009)
disco08_alle_indk	Occupational classification (2010)
hfaudd	Highest completed education
ansdage	Number of days employed
tilknyt	Primary workplace
	Firm-Level Variables
aar	Register or census year
adr	Other operating income
audg	Other social security costs
auer	Work carried out at own expense and listed under assets.
afat, atit	Investments
besk	Number of employees (in full-time equivalent hours)
dlg	Inventory change
ekud	Other external costs
otde	Ordinary losses on debtors
kene	Purchase of energy
kloe	Purchase of subcontracts and salary work (non-employees)
krhe	Purchase of raw materials, finished goods/packaging (ex. energy)
kvv	Purchase of goods for resale (commercial goods)
maat	Tangible fixed assets, end of year
oms	Turnover
pudg	Pension costs
seud	Secondary expenses
uasi	Expenses for the acquisition of small equipment
udhl	Expenses for rent
udvb	Expenses for employment agencies
ulol	Expenses for long-term rent and operational leasing
lgag	Salaries and wages
aneu, oeeu	Other external expenses

income of more than 30000 DKK, whose change in log annual full-time income from the previous year is between -1 and 2, who work at a firm with measures of estimated TFP (i.e. included in the firm sample above), and who are either classified as a full-time worker employed for the full year or make more than 150000 DKK in annual income at their primary job.

B Additional Tables and Figures

Table B.1 – Summary Statistics

	2000	2005	2010		2000	2005	2010
Panel A: Workers				Panel B: Firms			
Obs. (000s)	469.9	653.3	625.2	Obs. (000s)	29.6	45.2	48.3
% Women	28.0	30.0	31.0				
% High School	33.7	29.6	27.4	Firm Age: % Share of Firms			
				< 5	8.9	10.9	11.4
% Age groups				5-10	23.5	44.3	48.5
Below 25	8.69	6.7	8.1	10+	67.6	44.9	40.1
25-35	30.6	26.7	21.4				
36-45	27.0	30.9	31.4	Firm Age: % Share of Employment			
46-55	23.3	22.3	25.4	< 5	6.2	6.3	5.0
Above 55	10.3	13.4	14.0	5-10	35.7	33.9	34.9
				10+	58.2	59.9	60.1
Annual Labor Earnings							
Mean	49,513	53,104	54,176	Firm Size: % Share of Firms			
P10	34,544	35,954	35,954	20	83.0	84.1	87.4
P50	48,533	51,534	52,052	20-100	13.9	13.1	10.4
P90	77,653	83,283	87,553	100+	3.1	2.7	2.3
Hourly Wages				Firm: Size: % Share of Employment			
Mean	30.35	32.23	32.88	20	24.3	25.5	28.2
P10	20.97	21.82	21.82	20-100	28.1	28.8	26.6
P50	29.46	31.59	31.91	100-1000	36.7	35.2	33.3
P90	47.13	50.55	53.14	1000+	10.8	10.5	11.8

Note: Table B.1 shows different statistics for workers and firms in our baseline sample. All monetary values are converted to US dollars of 2010. To avoid the disclosure of any sensitive information, for all percentiles, we report the mean of all observations within a percentile-band rather than individual observations at the percentile cutoff.

Table B.2 – First-Stage Probit Estimates for Selection Model

Variable	Pr(Staying in Firm)	
	(1) Productivity Growth, $\Delta\nu_{jt}$	(2) Persistent Shock, η_{jt}
$\Delta\nu_{jt}$	.028	
	(.005)	
$\Delta\nu_{jt} \times I_{\Delta\nu_{jt}<0}$	.977	
	(.004)	
η_{jt}		.352
		(.006)
$\eta_{jt} \times I_{\eta_{jt}<0}$		1.175
		(.004)
ϵ_{jt}		.195
		(.004)
Age	-.003	-.004
	(.001)	(.001)
Male	-.132	-.153
	(.002)	(.002)
Lag Tenure	.040	.039
	(.000)	(.000)
Married	.027	.025
	(.003)	(.003)
Change Spouse	-.119	-.120
	(.011)	(.012)
Same Firm Spouse	.408	.457
	(.030)	(.030)
Spouse Firm's TFP (ν_{jt})	-.021	-.019
	(.002)	(.002)
Spouse Firm's ΔTFP ($\Delta\nu_{jt}$)	.010	.008
	(.003)	(.003)
Spouse Stayer	.028	.026
	(.003)	(.003)
Obs. (Millions)	7.04	7.04

Notes: Table B.2 shows selected parameter estimates from the first-stage probit model in Section 3.2. Robust standard errors are clustered at the firm level.

Table B.3 – Summary Statistics: Worker Hourly Wages and Firm TFP Shocks

	A: Workers Δw_{it}		B: Workers (Stayers)			Panel C: Firms		
Statistic	Stayers	Switchers	$\Delta\nu_{jt}$	η_j	ϵ_{jt}	$\Delta\nu_{jt}$	η_j	ϵ_{jt}
Mean	0.02	0.07	0.00	0.02	0.01	0.00	0.00	0.00
Std. Dev.	0.18	0.36	0.26	0.27	0.20	0.24	0.19	0.17
P10	-0.14	-0.30	-0.25	-0.27	-0.16	-0.23	-0.16	-0.17
P25	-0.05	-0.11	-0.12	-0.13	-0.07	-0.10	-0.08	-0.08
P50	0.01	0.06	0.00	0.00	0.01	0.00	0.00	0.00
P75	0.08	0.23	0.12	0.14	0.09	0.10	0.07	0.08
P90	0.18	0.46	0.26	0.34	0.18	0.22	0.19	0.17
Obs. (Millions)	6.47	0.56	6.47	6.47	6.47	0.57	0.57	0.57

Note: Panel A shows sample statistics for workers' log hourly wage growth for stayers ($\Delta w_{ijt} = \log(w_{ijt}) - \log(w_{ijt-1})$) and for switchers ($\Delta w_{ijt} = \log(w_{ijt}) - \log(w_{ikt-1})$). Panel B shows moments of workers' firm productivity (i.e. workers are assigned the productivity of the firm where they work). Panel C shows the distribution of firm productivity. (Pseudo) Percentiles report the mean within a band around the corresponding percentile to preserve confidentiality.

Table B.4 – Passthrough to Hours and Annual Wages

	(1) Annual	(2) Hourly	(3) Hours	(4) Annual	(5) Hourly	(6) Hours
η_{jt}	.118	.082	.037	.061	.064	−.002
	(.014)	(.007)	(.008)	(.005)	(.004)	(.006)
$\eta_{jt} < 0$				.253	.082	.172
				(.009)	(.008)	(.007)
R^2	.700	.227	.770	.703	.228	.771
Obs. (Million)	6.5	6.5	6.5	6.5	6.5	6.5

Note: Table B.4 shows a set of passthrough regressions using annual wages (columns 1 and 4), hourly raw wages (columns 2 and 5) and hours (columns 3 and 6) as independent variables. All regressions include firm-level controls (which include, firm age, lagged firm shocks, and firm employment), worker-level controls (which include, a polynomial in age, lagged worker experience, lagged log wage level, lagged tenure in the firm, and gender), and year fixed effects. These results are all selection corrected. Robust standard errors are clustered at the firm-level.

Table B.5 – High-Wage Workers are More Affected by Selection

	Uncorrected					Selection Corrected				
	(Q1)	(Q2)	(Q3)	(Q4)	(Q5)	(Q1)	(Q2)	(Q3)	(Q4)	(Q5)
η_{jt}	.038	.040	.032	.033	.052	.042	.042	.041	.062	.129
	(.005)	(.004)	(.004)	(.004)	(.006)	(.005)	(.004)	(.004)	(.004)	(.008)
$\eta_{jt} < 0$	−.003	−.024	−.012	−.018	−.032	.024	.015	.065	.061	.061
	(.009)	(.007)	(.007)	(.007)	(.013)	(.010)	(.008)	(.008)	(.008)	(.011)
$\hat{\lambda}$						-.071	-.085	-.167	-.237	-.565
						(.013)	(.009)	(.011)	(.013)	(.030)
N	1.1M	1.2M	1.3M	1.4M	1.4M	1.1M	1.2M	1.3M	1.4M	1.4M
R^2	.75	.82	.83	.82	.74	.75	.82	.83	.82	.74

Table B.5 shows the passthrough regression results for η_{jt} for different quintiles of the (lagged) wage distribution. Columns 1-5 are OLS regressions without selection correction, while columns 6-10 are selection corrected. All regressions include firm-level controls (which include, firm age, lagged firm shocks, and firm employment), worker-level controls (which include, a polynomial in age, lagged worker experience, lagged log wage level, lagged tenure in the firm, and gender), and year fixed effects. Robust standard errors are clustered at the firm-level.

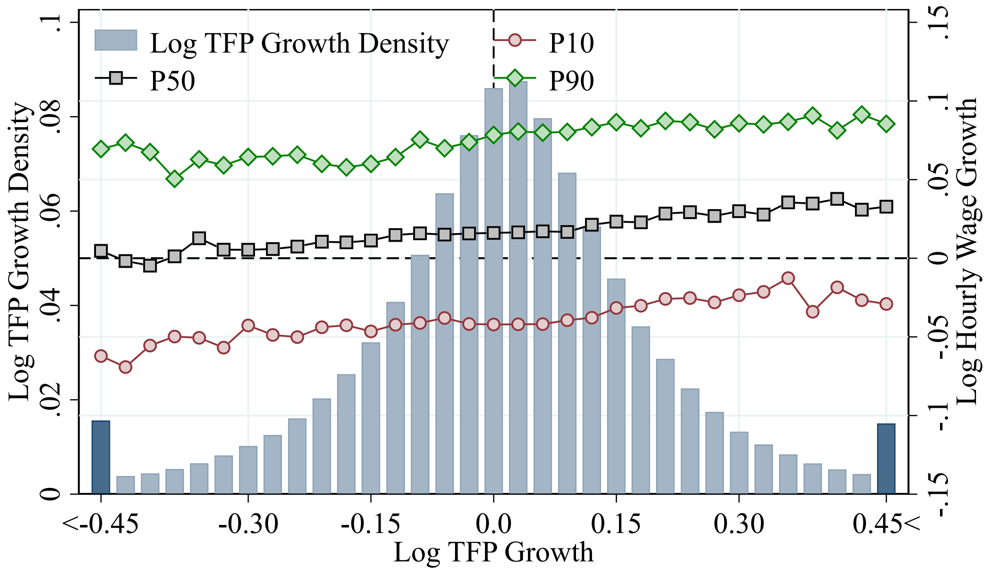
Table B.6 – Baseline Results with Alternative Weighting

	Weighted by $1/\text{EMP}_{jt-1}$				Weighted by $1/\text{Stayers Share}_{jt}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
η_{jt}	.087	.147	.096	.121	.028	.073	.038	.058
	(.003)	(.003)	(.003)	(.004)	(.004)	(.006)	(.005)	(.005)
$\eta_{jt} < 0$			-.018	.070			-.019	.068
			(.005)	(.006)			(.009)	(.007)
$\hat{\lambda}_{ijt}$		-.275		-.302		-.166		-.234
		(.010)		(.011)		(.018)		(.014)
R^2	.73	.74	.73	.74	.78	.78	.78	.78

Note: Table B.6 reports passthrough regression results for η_{jt} under two alternative weighting schemes. Columns 1-4 weight observations by the inverse of lagged firm employment, $1/\text{EMP}jt-1$, while columns 5-8 weight by the inverse of the share of workers who remain with the firm from $t-1$ to t, $1/\text{Stayers Share}jt$. All specifications include firm-level controls (firm age, lagged firm shocks, and firm employment), worker-level controls (a polynomial in age, lagged experience, lagged log wage, lagged tenure, and gender), and year fixed effects. Estimates including $\hat{\lambda}_{ijt}$ are selection-corrected, and robust standard errors clustered at the firm level are shown in parentheses.

Figure B.1 – Wage Change Percentiles Across the TFP Change Distribution

(a) Hourly Wages



(b) Residual Hourly Wages

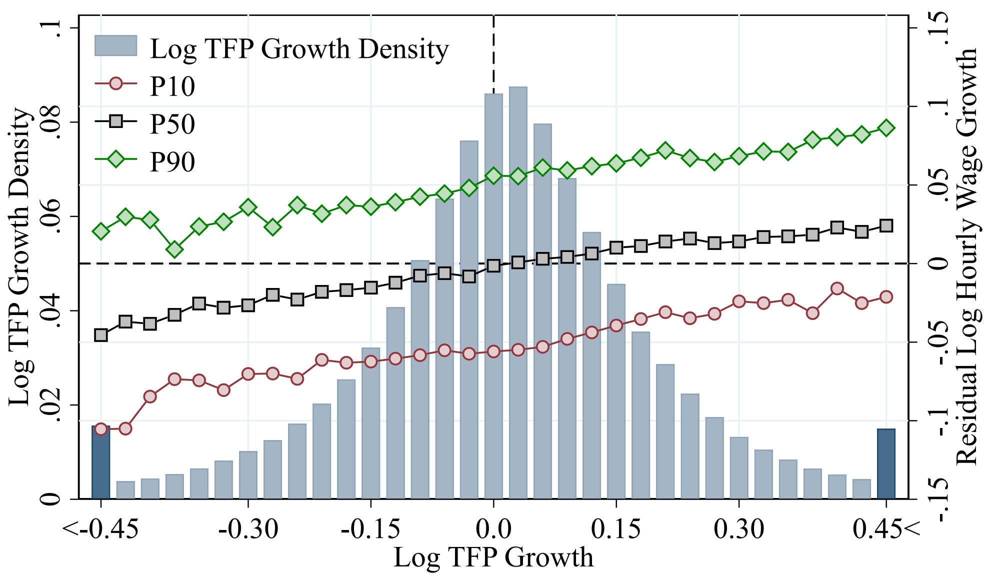
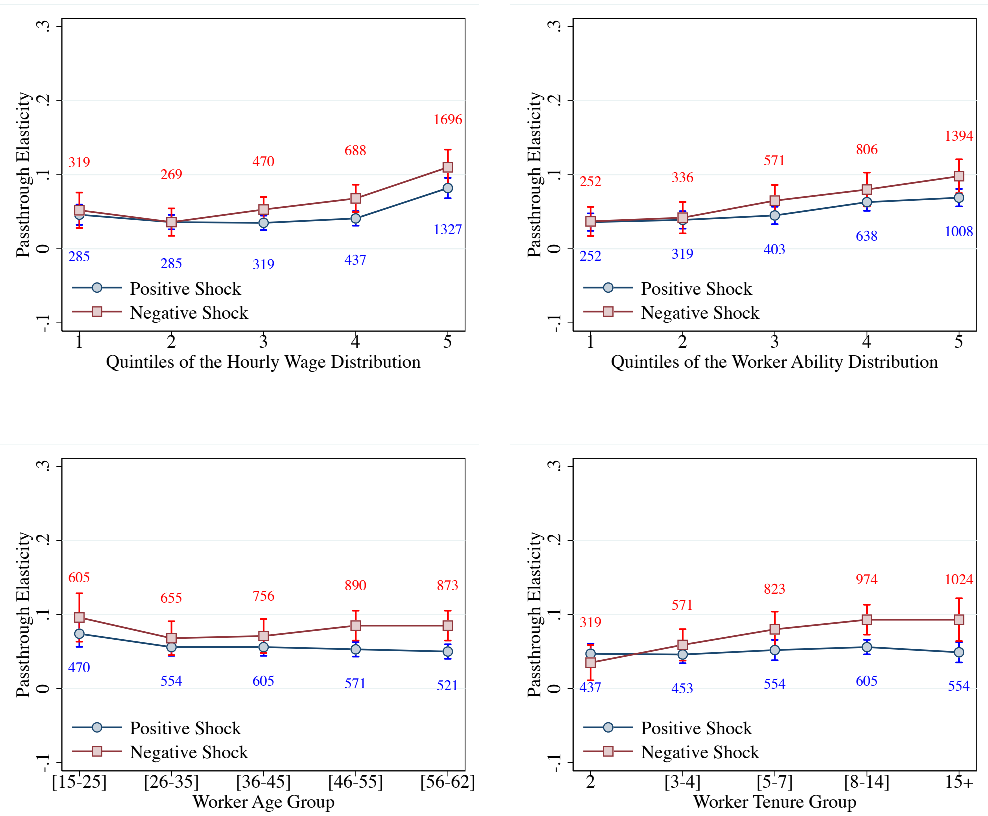


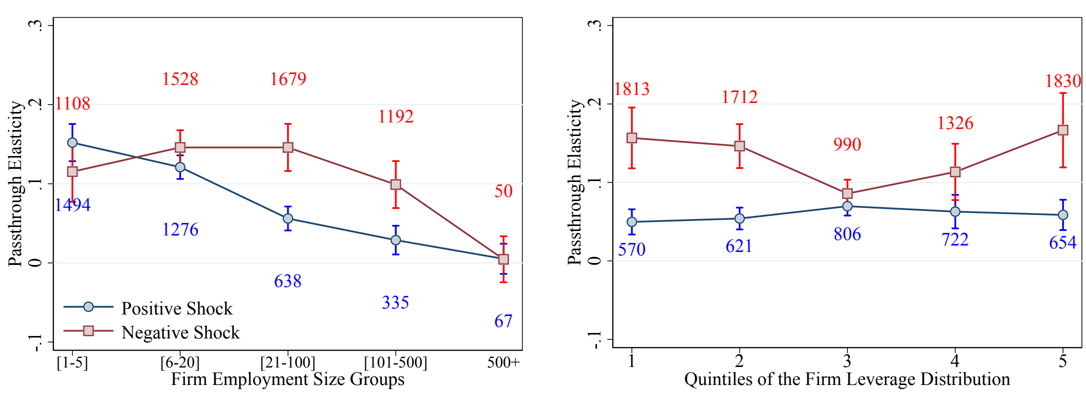
Figure B.1 is based on a pooled sample of firms and workers between the years 1996 to 2010. The blue bars show log TFP growth distribution (the left y axis). We separate firms into 41 equally sized bins between -.45 and 45. The left- and right-most bins, marked in darker blue, contain the remaining left and right tails of the distribution. The right y axis of each panel shows the within-percentiles means of the hourly wage growth (top panel) and hourly wage growth after controlling for worker characteristics, firm characteristics, and endogenous selection. Hourly wage growth measures are calculated for stayers (workers for whom the firm providing the higher total annual earnings was the same in periods t and $t-1$).

Figure B.2 – Worker Heterogeneity: Passthrough from Transitory TFP Shocks



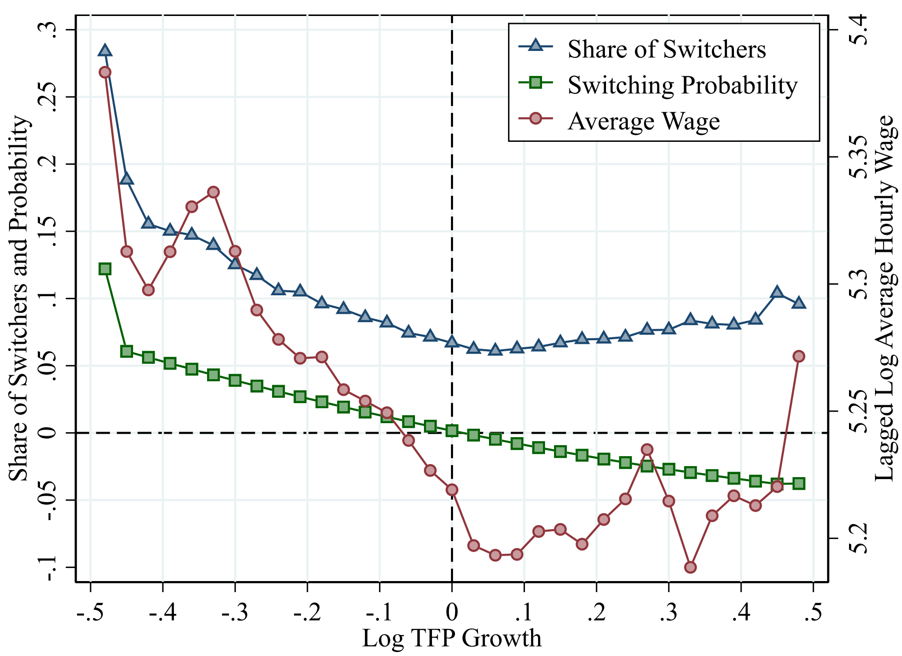
Note: Figure B.2 shows the elasticity of hourly wages to transitory TFP shocks (ϵ_{jt}) across different dimensions of worker heterogeneity. The vertical lines show 95% confidence intervals around the point estimates. In each plot, the numbers represent the monetary value (in 2010 US$) of a shock of one standard deviation calculated using the corresponding elasticity.

Figure B.3 – Persistent Shocks by Firm Size and Leverage



Note: Figure B.3 shows the elasticity of hourly wages across workers employed in firms with different characteristics. Panel A shows the passthrough within firms of different employment size and Panel B by firm leverage. The vertical lines show 95% confidence intervals around the point estimates. In each plot, the numbers represent the monetary value (in 2010 US$) of a shock of one standard deviation calculated using the corresponding elasticity.

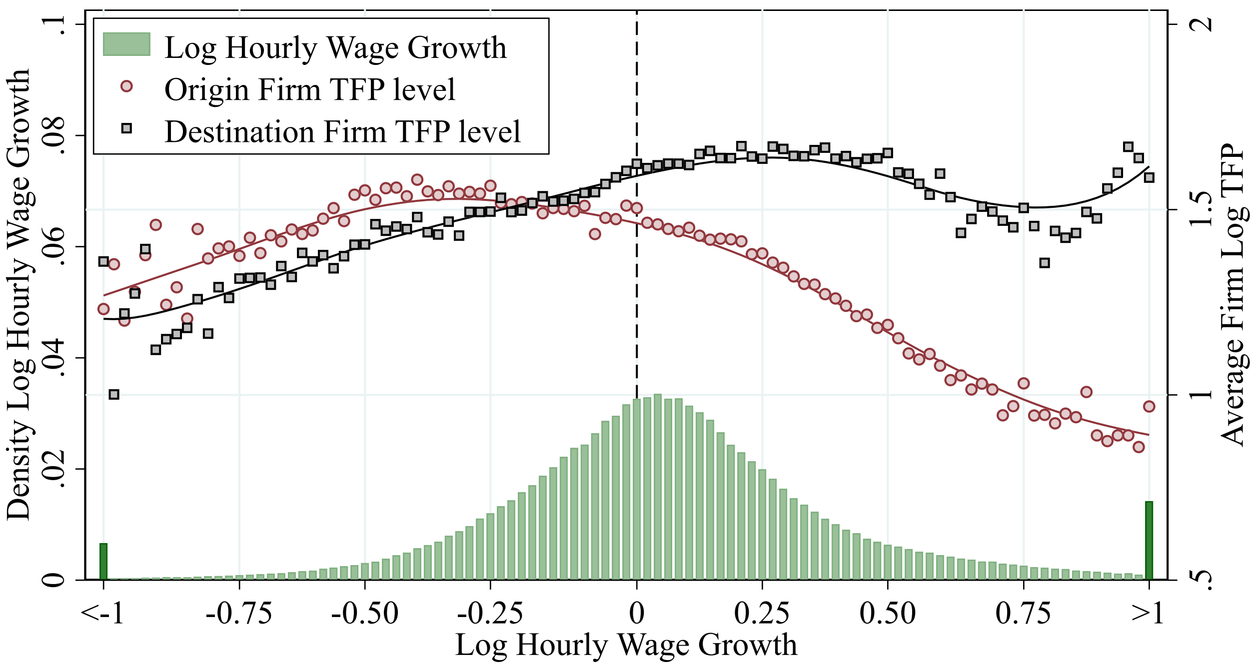
Figure B.4 – Switching Probability, Wages, and Firm Growth



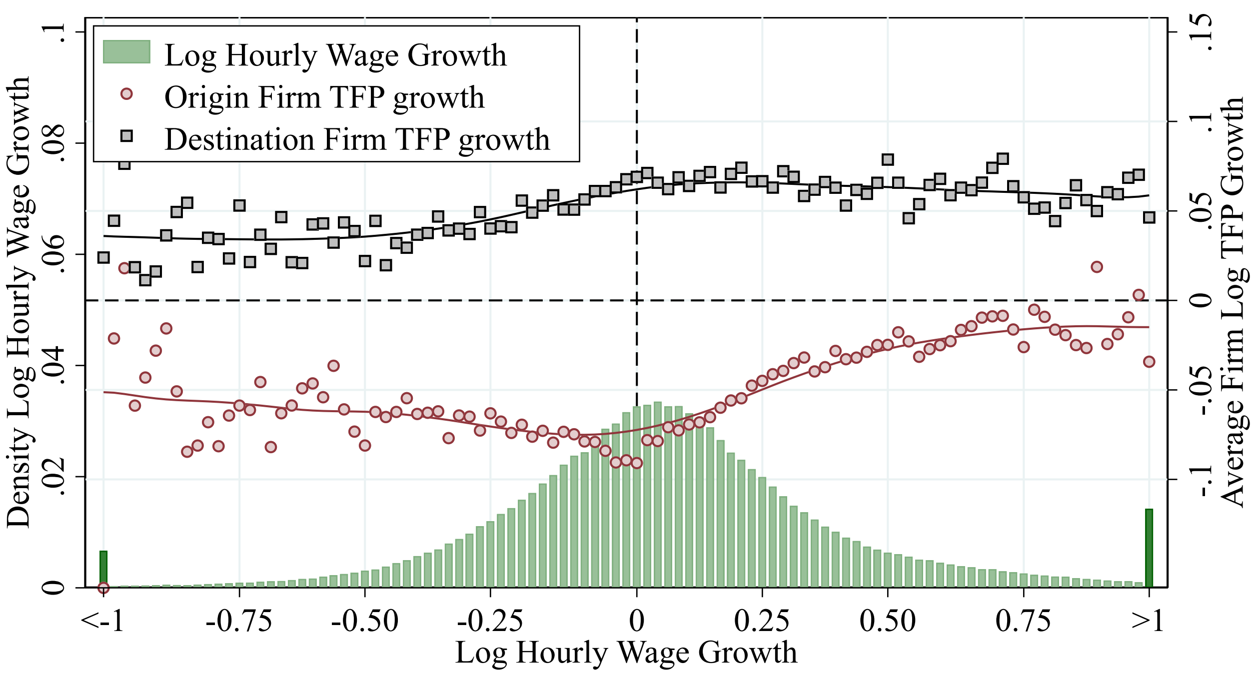
Note: Figure B.4 shows the predicted probability of switching and the empirical share of switchers (left axis) and the lagged average wages of switchers (right axis) conditional on the change in residualized firm-level productivity.

Figure B.5 – Log Hourly Wage Growth For Switchers and Firm TFP

(a) TFP Level



(b) TFP Growth



Note: Figure B.5 is based on a pooled sample of switchers and their corresponding firms. The green bars show the share of switchers within different bins of the log hourly wage growth distribution (left y-axis). To construct the graph, we partition the wage growth distribution into 101 equally-spaced bins between -1 and 1. The left- and right-most bins encompass the remaining left and right tails of the distribution. In Panel A (Panel B) the red dots show the average log TFP (average log TFP growth) of the firms that employed the workers in the corresponding wage change bin in period $t-1$. The black squares show the average TFP (average log TFP growth) for the firms that employed the workers in each bin in period t.

C Additional Results and Analysis

C.1 Alternative Measures of Passthrough

Value Added, Hours, and Worker Ability. Our empirical approach differs in several ways from the standard methods used in the rent-sharing literature. In this Appendix, we examine how each of these factors contributes to our results. To do this, we begin with a simple OLS regression of changes in (log) total annual income on changes in (log) firm value added, controlling for individual and firm observables as in our baseline results. As shown in column 1 of Table C.1, we find significant passthrough from changes in value added to annual income–an elasticity of 0.079, which implies that a one standard deviation change in value added leads to an average change in income of $1,911 US dollars. However, this effect could be due to a number of factors (e.g., changes in annual income due to a change in hours worked by the individual, either voluntarily or because of a change in labor demand).

The change in value added also includes planned shifts in labor demand, which means that a significant portion of the measured elasticity may be the mechanical link between changes in labor captured by changes in value added, and shifts in hours for workers captured in annual income. Column 2 shows the results of regressing changes in annual income on changes in residual value added, which is the predicted residual from a regression of (log) value added on logs of firm capital and labor (measured in full-time equivalents). This strips variation in inputs out of the firm shock and reduces the elasticity to 0.063. However, the change in annual income still combines changes in hourly wage and hours on the worker side.

To decompose how much of the passthrough from shocks to income is due to extensive-margin adjustment in labor demand versus changes in the wage rate, we substitute the dependent variable with changes in the log hourly wage (column 3 of Table C.1). We find that a little more than half of the passthrough to annual income from changes in residual value added is due to changes in the hourly wage, while the rest is due to changes in hours worked (we find similar results when using our measures of firm shocks and wages).

When we additionally eliminate variation in worker ability at the firm level by using our ability-adjusted measure of labor input, a_{jt}, when calculating the value added residual (column 4), passthrough decreases from 0.035 to 0.032. Since passthrough and firm shocks may be related to worker ability, we then add in controls for individual ability (column 5) and find a significant increase in passthrough to 0.042. Finally, column 6 shows the results when we use our fully corrected measure of firm shocks–changes in ability-adjusted TFP ($\Delta\nu_{jt}$) which, unlike the value added residuals from the other regressions, is allowed to be correlated with input adjustments. This increases the estimated passthrough to 0.046, which matches the passthrough estimate before we correct for workers' mobility, shown in column 5 of Table I. These results indicate that failing to correct for changes in hours will lead to significant overestimates of passthrough, while not correcting for worker-level ability and mismeasurement of firm shocks will significantly underestimate passthrough.

Changes in Persistent and Transitory Components. One caveat to interpret our passthrough results from η_{jt} and ϵ_{jt} is that they represent the innovation components of the TFP measure ν_{jt}, which do not directly add up to the total changes of the TFP ($\Delta\nu_{jt}$). To complete our analysis, we further investigate the passthrough elasticities from the two components that come directly from decomposing $\Delta\nu_{jt} = \Delta\omega_{jt} + \Delta\epsilon_{jt}$, and estimate:

$$\Delta\hat{w}_{ijt} = \beta_0 + \beta^{\Delta\omega}\Delta\omega_{jt} + \beta^{\Delta\epsilon}\Delta\epsilon_{jt} + Z_{jt}\Gamma + X_{it}\Omega + \rho\hat{\lambda}_{ijt} + \delta_t + \zeta_{ijt}, \tag{10}$$

This equation mimics Equation 8 in all controls except the persistent and transitory measures. The results are shown in columns 1 and 2 of Table C.2. The estimated passthrough elasticities are slightly lower than the passthrough elasticities from our baseline measure (columns 3 and 4 in Table I) though the differences are statistically insignificant. We also estimate passthrough from the sum of the persistent and transitory shocks, $\eta_{jt} + \epsilon_{jt}$, as another measure of the total effect of TFP shocks on wages. The results (columns 3 and 4 of Table C.2) are slightly lower than the results for ν_{jt} in Table I.

Additional Measures of Productivity. For robustness, we also use an alternative TFP estimator to investigate the passthrough elasticity. Specifically, we use the Blundell and Bond (2000) AR(1) estimator (a method which is robust to firm-level output market power), and present the results in Table C.3. For easier comparison, we also include our main estimates. Columns 5 and 6 contain the selection-corrected estimates using the Blundell and Bond (2000) method, showing that average passthrough is significant and is larger for negative shocks, similar to our baseline results. Columns 7 and 8 show that the asymmetry disappears if one does not control for selection.

C.2 Aggregate and Industry Shocks

In this section, we study the impact of aggregate and industry shocks on workers' wages. Separating their effect is important, as there might be general equilibrium effects that confound our passthrough estimates. To separate the effect of aggregate- and industry-level fluctuations in productivity, we follow Carlsson et al. (2015) and first regress our firm-level productivity changes on a set of year dummies and calculate the residual change, which is orthogonal to the aggregate cyclical variation in TFP. We then regress those residual changes on a full set of year-industry dummies at the 2-digit NACE code level. The predicted values from this regression give us our measure of industry-level TFP shocks (denoted by $\Delta\nu_t^k$), where the residuals are our measure of idiosyncratic firm-level changes in TFP (denoted by $\Delta\nu_{jt}^f$) which are orthogonal to industry and aggregate fluctuations.

Finally, we regress the change in log hourly wages on these measures of firm- and industry-level productivity shocks. As column (1) of Table C.4 shows, the elasticity of wages to firm-level shocks (after we have stripped out the year and industry components) is essentially the same as in our baseline results (column (1) of Table I), indicating that aggregate shocks play a minor role in our results. Changes in average productivity at the industry-level have a significant impact on workers' wages, although the passthrough is less than a third of the passthrough from idiosyncratic shocks. Furthermore, if we separate positive from negative shocks, we find that only negative industry productivity changes have an impact on workers' wages. The economic impact is small since there is little variation in the industry-level productivity, relative to the aggregate and idiosyncratic variation.

These results depart somewhat from other estimates in the literature which typically find a larger role for industry shocks in wage changes. Notably, Souchier (2023) find passthrough rates of idiosyncratic and industry value added shocks to (residualized) worker annual income of 4.6% and 18.5% respectively. Our results differ for several reasons, primarily due to our use of hourly wages, firm-level TFP, and controls for individual ability. Table C.5 shows

Table C.1 – Comparing Passthrough Under Different Assumptions

	(1) $\Delta w^a_{i,j,t}$	(2) $\Delta w^a_{i,j,t}$	(3) $\Delta w_{i,j,t}$	(4) $\Delta w_{i,j,t}$	(5) $\Delta w_{i,j,t}$	(6) $\Delta w_{i,j,t}$
β	.079	.063	.035	.032	.042	.046
	(.002)	(.002)	(.001)	(.001)	(.002)	(.003)
Firm shock	VA	VAres	VAres	VAres$_a$	VAres$_a$	$\Delta\nu_{jt}$
Individual Ability	N	N	N	N	Y	Y
R^2	.49	.49	.17	.18	.79	.78
Pct Effect	3.4%	2.6%	1.5%	1.6%	2.1%	1.2%
Avg. Effect	$1,911	$1,492	$873	$955	$1,243	$705
Correction	None	Residual	Hours	Quality	Quality	TFP

Note: Table C.1 shows a set of OLS panel regressions controlling for firm and worker characteristics. $w^a_{i,j,t}$ and $w_{i,j,t}$ are log annual income and log hourly wages, respectively. Firm shocks are changes in logs of: value added (VA), residualized value added from an OLS regression of value added on firm inputs (VAres), residualized value added using the ability-adjusted measure of labor (VAres$_a$), and ability-adjusted total TFP (ν_{jt}). All regressions include firm-level controls (firm age, lagged firm shocks, firm employment), worker-level controls (polynomial in age, lagged experience, lagged log wage, lagged tenure, gender), and year fixed effects. These results are not selection corrected. Robust standard errors are clustered at the firm level.

the results of several regressions of annual income and hourly wages on differing measures of firm and industry performance. When we regress changes in annual income on changes in value added (column 1), we also find a larger passthrough of industry vs idiosyncratic shocks (27.1% vs 7.6%). If we residualize value added on firm-level capital and labor inputs, passthrough of industry shocks to annual income declines to 11.7% (column 2). Columns 1 and 2 are the closest to the setting in Souchier (2023) and provide very similar results. Moving to hourly wages (column 3) further reduces passthrough of industry shocks to 3.9%, similar in magnitude to the passthrough of idiosyncratic shocks. Once we control for individual ability (column 4) and use change in total productivity (column 5), idiosyncratic shocks have greater passthrough than industry shocks. Further controlling for selection bias (see Table C.4) increases passthrough of idiosyncratic shocks but does not significantly change measured passthrough of industry shocks.

Table C.2 – Passthrough from Alternate Measures of TFP to Wages

Dep. Variable:	(1) $\Delta\hat{w}_{ijt}$	(2) $\Delta\hat{w}_{ijt}$	(3) $\eta_{jt}+\epsilon_{jt}$	(4) $\eta_{jt}+\epsilon_{jt}$
$\Delta\omega_{jt}$	.072	.055		
	(.006)	(.004)		
$\Delta\omega_{jt} \times I_{\Delta\omega_{jt}<0}$		.066		
		(.007)		
$\Delta\epsilon_{jt}$	.033	.025		
	(.003)	(.005)		
$\Delta\epsilon_{jt} \times I_{\Delta\epsilon_{jt}<0}$		.017		
		(.008)		
$\eta_{jt}+\epsilon_{jt}$			.062	.036
			(.004)	(.005)
$(\eta_{jt}+\epsilon_{jt}) \times I_{\eta_{jt}+\epsilon_{jt}<0}$				.087
				(.006)
R^2			.79	
Obs. (Millions)			6.5	

Note: Table C.2 presents passthrough estimates for alternate measures of the persistent and transitory shocks to firm TFP, controlling for firm and worker characteristics. All regressions include firm-level controls (i.e., firm age, lagged firm TFP level, lagged firm employment (measured by total number of hours), and lagged total firm ability (L_{jt-1})), worker-level controls (i.e., a polynomial in age, lagged worker experience, lagged log wage level, lagged tenure in the firm, gender, and lagged log ability), the inverse of the Mills ratio to control for selection, and year fixed effects. The sample is conditional on staying at the firm. All estimates are selection corrected. Robust standard errors in parentheses are clustered at the firm-level.

Table C.3 – Passthrough with Blundell–Bond TFP Estimator

	Baseline				Blundell–Bond			
	Selection Corrected		Uncorrected		Selection Corrected		Uncorrected	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All	Pos/Neg	All	Pos/Neg	All	Pos/Neg	All	Pos/Neg
$\Delta\nu_{jt}$	.076	.060	.046	.062	.062	.036	.047	.051
	(.004)	(.004)	(.003)	(.004)	(.003)	(.004)	(.002)	(.004)
$\Delta\nu_{jt} < 0$		.053		-.032		.069		-.007
		(.005)		(.005)		(.005)		(.005)
R^2	.78	.78	.78	.78	.79	.79	.79	.79

Note: Table C.3 presents passthrough elasticities estimated with our baseline TFP measure (columns 1-4) and with a Blundell–Bond GMM TFP estimator (columns 5-8). Each panel reports results both with and without selection correction and distinguishes average passthrough from the incremental effect under negative productivity shocks. All regressions control for firm characteristics (age, lagged shocks, employment), worker characteristics (age polynomial, experience, lagged wage, tenure, gender), and year fixed effects. Robust standard errors are clustered at the firm level.

Table C.4 – Passthrough from Firm and Industry TFP shocks to Wages

Dep. Variable	Change in Log Hourly Wages, $\Delta\hat{w}_{i,j,t}$	
	(1)	(2)
Specification:	All	Pos/Neg
$\Delta\nu^f_{jt}$	.076	.058
	(.004)	(.004)
$\Delta\nu^f_{jt} \times \mathbb{I}_{\Delta\nu_{jt}<0}$		.060
		(.006)
$\Delta\nu^k_t$	.024	.00
	(.006)	(.015)
$\Delta\nu^k_t \times \mathbb{I}_{\Delta\nu^k_t<0}$		.046
		(.023)
$\hat{\lambda}_{it}$	$-.209$	$-.275$
	(.014)	(.016)
R^2	.78	.78
Obs. (Millions)	6.47	6.47
Monetary Value of a Shock to Firm TFP (US$ 2010)		
$\Delta\nu_{jt}$	$1,041	
$\Delta\nu_{jt} > 0$		$789
$\Delta\nu_{jt} < 0$		$1,595
$\Delta\nu^k_t$	$67.2	
$\Delta\nu^k_t > 0$		$0.0
$\Delta\nu^k_t < 0$		$117

Note: Table C.4 shows a set of OLS panel regressions of idiosyncratic and industry-level TFP shocks on log hourly wages, controlling for firm and worker characteristics as in our baseline specification in Table I. All estimates are selection corrected. Robust standard errors are clustered at the firm-level.

Table C.5 – Passthrough of Idiosyncratic vs. Industry Shocks

	(1)	(2)	(3)	(4)	(5)
	Δw^a_{ijt}	Δw^a_{ijt}	Δw_{ijt}	Δw_{ijt}	Δw_{ijt}
Idiosyncratic shock (β^{id})	0.076	0.062	0.035	0.042	0.047
	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)
Industry shock (β^{ind})	0.271	0.117	0.039	0.034	0.018
	(0.015)	(0.024)	(0.012)	(0.015)	(0.006)
Model details					
Firm shock	VA	VA_{res}	VA_{res}	$\text{VA}_{\text{res,a}}$	$\Delta\nu_{jt}$
Individual ability	N	N	N	Y	Y
R^2	0.491	0.491	0.170	0.786	0.783
Correction	None	Residual	Hours	Quality	TFP

Note: Table C.5 presents passthrough of different measures of firm shocks to wages. Each column reports OLS passthrough estimates from the listed firm-level shock to worker pay. Annual income is w^a_{ijt}; hourly wage is w_{ijt}. VA_{res} denotes residualized value added, and $\text{VA}_{\text{res,a}}$ controls for worker ability. $\Delta\nu_{jt}$ is the change in total ability-adjusted TFP. Each column includes corrections from previous columns. All specifications include the same controls as in our baseline specification. Robust standard errors are clustered at the firm level.

D Selection Bias in the Simple Logit Model

In this appendix, we derive and provide intuition for why the presence of selection will generate biased estimates of the passthrough elasticity in the context of a simple logit model of labor supply with homogeneous passthrough elasticities.

First, we sketch the general labor supply model and establish a result regarding the probability of staying. Assume that a labor market is populated by N workers and J firms. Workers can choose to work for any firm j or choose non-employment ($j = 0$) in each period t. The utility of job j to worker i in period t is $U_{ijt} = V_{ijt} + \eta^u_{ij}$, where V_{ijt} is the observed component including wages and other non-pecuniary benefits or job amenities, and η^u_{ij} is the individual utility gained by worker i at firm j, which is only observed by the worker. The probability that a worker is a *stayer* in period t—i.e., remains in the same firm that the worker was employed at in period $t-1$—is then the probability that j is the preferred job in t conditional on j also being the preferred job in $t-1$. Let $S_{ijt} = 1$ when a worker is a stayer. Then,

$$\Pr(S_{ijt} = 1) = \Pr(\eta^u_{ik} < \eta^u_{ij} + V_{ijt} - V_{ikt} \forall k \neq j | \eta^u_{ik} < \eta^u_{ij} + V_{ijt-1} - V_{ikt-1} \forall k \neq j)$$

Define $\Delta X_t = X_t - X_{t-1}$ and $I_{it} = \sum_k e^{V_{ikt}}$. If η^u_{ij} are i.i.d., following a standard Gumbel distribution, then we have the following result:

Proposition D.1. *The conditional probability that a worker stays in job j in t given they chose j in $t-1$ is* $\Pr(S_{ijt} = 1) = \Lambda(\Delta V_{ijt} - \Delta \log I_{it})$ *where* $\Lambda(z) = \frac{1}{1+e^{-z}}$ *is the standard logistic CDF.*

Proof. The conditional probability of staying is

$$\frac{\Pr(\eta^u_{ik} < \eta^u_{ij} + V_{ijt} - V_{ikt} \forall k \neq j \quad \cap \quad \eta^u_{ik} < \eta^u_{ij} + V_{ijt-1} - V_{ikt-1} \forall k \neq j)}{\Pr(\eta^u_{ik} < \eta^u_{ij} + V_{ijt-1} - V_{ikt-1} \forall k \neq j)} \tag{11}$$

First, we derive the numerator as follows:

$$
\begin{aligned}
&\Pr(\eta^u_{ik} < \eta^u_{ij} + V_{ijt} - V_{ikt} \forall k \neq j \quad \cap \quad \eta^u_{ik} < \eta^u_{ij} + V_{ijt-1} - V_{ikt-1} \forall k \neq j) \\
=&\int \prod_{k\neq j} F(\eta^u_{ij} + V_{ijt} - V_{ikt}) \prod_{k\neq j} F(\eta^u_{ij} + V_{ijt-1} - V_{ikt-1}) e^{-e^{-\eta^u_{ij}}} e^{-\eta^u_{ij}} d\eta^u_{ij} \\
=&\int \prod_{k\neq j} e^{-e^{-\eta^u_{ij}}(e^{-(V_{ijt}-V_{ikt})}+e^{-(V_{ijt-1}-V_{ikt-1})})} e^{-e^{-\eta^u_{ij}}} e^{-\eta^u_{ij}} d\eta^u_{ij} \\
=&\int \exp\left(-e^{-\eta^u_{ij}} \sum_k \left(e^{-(V_{ijt}-V_{ikt})} + e^{-(V_{ijt-1}-V_{ikt-1})}\right)\right) e^{-\eta^u_{ij}} d\eta^u_{ij} \\
=&\int_0^\infty \exp\left(-t \sum_k \left(e^{-(V_{ijt}-V_{ikt})} + e^{-(V_{ijt-1}-V_{ikt-1})}\right)\right) dt \\
=&\frac{\exp(-t\sum_k \left(e^{-(V_{ijt}-V_{ikt})} + e^{-(V_{ijt-1}-V_{ikt-1})}\right))}{\sum_k \left(e^{-(V_{ijt}-V_{ikt})} + e^{-(V_{ijt-1}-V_{ikt-1})}\right)}\Big|_0^\infty \\
=&\frac{1}{\sum_k \left(e^{-(V_{ijt}-V_{ikt})} + e^{-(V_{ijt-1}-V_{ikt-1})}\right)} \\
=&\frac{e^{V_{ijt-1}}}{e^{-\Delta V_{ijt}} I_{it} + I_{it-1}}
\end{aligned}
$$

Similarly, one can show that $\Pr(\eta^u_{ik} < \eta^u_{ij} + V_{ijt-1} - V_{ikt-1} \forall k \neq j) = \frac{e^{V_{ijt-1}}}{I_{it-1}}$. This provides

$$
\Pr(S_{ijt} = 1) = \frac{\frac{e^{V_{ijt-1}}}{e^{-\Delta V_{ijt}} I_{it} + I_{it-1}}}{\frac{e^{V_{ijt-1}}}{I_{it-1}}} = \frac{I_{it-1}}{e^{-\Delta V_{ijt}} I_{it} + I_{it-1}} = (1 + e^{-(\Delta V_{ijt} - \Delta \log I_{it})})^{-1} \tag{12}
$$

which is the standard Logistic CDF. □

Given this result, consider the following passthrough regression,

$$
\Delta \log W_{ijt} = \varepsilon^W_A \Delta \log A_{jt} + \Delta X_{ijt}\Gamma + \epsilon_{ijt}, \tag{13}
$$

where X_{ijt} are observable worker and firm characteristics, A_{jt} is the firm's j productivity, and ϵ_{ijt} contains unobserved determinants of the change in wage, assumed to be uncorrelated in the population with ΔX_{ijt} and $\Delta \log A_{jt}$. The conditional expectation of $\Delta \log W_{ijt}$ given ΔA_{jt}, ΔX_{ijt} and the probability that $\Delta \log W_{ijt}$ is observed is

$$
\mathbb{E}[\Delta \log W_{ijt} | \Delta A_{jt}, \Delta X_{ijt}, S_{ijt} = 1] = \varepsilon^W_A \Delta \log A_{jt} + \Delta X_{ijt}\Gamma + \mathbb{E}[\epsilon_{ijt} | S_{ijt} = 1] \tag{14}
$$

Since $\Pr(S_{ijt} = 1)$ is in principle a function of $\Delta \log W_{ijt}$ through ΔV_{ijt}, the fact that some components of $\Delta \log W_{ijt}$ are unobserved will lead to biased estimates of ε_A^W. We can gain intuition about the potential mechanisms and sign of the bias using several examples. In the first example, selection will bias estimates of the passthrough elasticity up, while in the second example, the bias will be down towards zero.

D.1 Example 1

Suppose the utility from employment at firm j depends on the log wage (W_{jt}) and some common exogenous job amenity B_{jt},

$$U_{ijt} = \theta \log W_{jt} + \log B_{jt} + \eta_{ij}^u = V_{jt} + \eta_{ij}^u \tag{15}$$

with $\theta > 0$. This provides the firm-level labor supply $g(W_{jt}) = L_{jt} = B_{jt} W_{jt}^{\theta} N_t I_t^{-1}$ where we assume firms are atomistic and take the market wage index I_t as given. Each firm operates a simple revenue production function $Y_{jt} = A_{jt} L_{jt}^{\alpha}$ where $A_{jt} > 0$ represents firm-specific revenue shifters (such as productivity or demand shocks), and $\alpha \in (0, 1)$ determines the returns to scale in labor. Firms choose wages to solve the following profit maximization problem (here we suppress the subscripts for clarity):

$$\max_W \{Ag(W)^{\alpha} - Wg(W)\}$$

which provides the following first-order condition:

$$\alpha A g(W)^{\alpha-1} = W \times \left(\frac{1 + \epsilon_W^L}{\epsilon_W^L} \right). \tag{16}$$

Since the labor supply curve is log-linear in wages, the labor supply elasticity is a constant: $\epsilon_W^L = \frac{dg(W)}{dW} \frac{W}{g(W)} = \theta$. Plugging in for $g(W)$ and ϵ_W^L and rearranging Equation (16) provides the solution to the firm's optimal wage:

$$W^* = \left(A\alpha \frac{\theta}{1+\theta} \tilde{B}^{\alpha-1} \right)^{\frac{1}{1+\theta(1-\alpha)}}$$

This provides a passthrough elasticity of

$$\epsilon_A^w = \frac{dW}{dA}\frac{A}{W} = \frac{1}{1+\theta(1-\alpha)} \tag{17}$$

which does not depend on firm characteristics and is constant across firms within the labor market.

Suppose now we want to estimate the elasticity of wages with respect to TFP shocks using the regression,

$$\Delta \log W_{jt} = \varepsilon_A^W \Delta \log A_{jt} + (\alpha - 1)\varepsilon_A^W \Delta \log B_{jt} + \Delta C_t \tag{18}$$

where $C_t = \varepsilon_A^W \log \left(\alpha \frac{\theta}{1+\theta} \left(\frac{N_t}{I_t} \right)^{\alpha-1} \right)$, and the probability of staying is

$$S_{ijt} = 1 \iff \tilde{\eta}_{ij}^u \leq \theta \varepsilon_A^W \Delta \log A_{jt} + \Delta C_t - \Delta \log I_t + (1 + \theta(\alpha - 1)\varepsilon_A^W)\Delta \log B_{jt} \tag{19}$$

where $\tilde{\eta}_{ij}^u \sim \Lambda$ (standard logistic). We can rewrite this expression as

$$S_{ijt} = 1 \iff \theta \varepsilon_A^W \Delta \log A_{jt} \geq \tilde{\eta}_{ij}^u - \Delta C_t + \Delta \log I_t - (1 + \theta(\alpha - 1)\varepsilon_A^W)\Delta \log B_{jt} \tag{20}$$

Since $1 + \theta(\alpha - 1)\varepsilon_A^W > 0$, this means $\Delta \log B_{jt}$ and $\Delta \log A_{jt}$ will be negatively correlated in the sample. Intuitively, firms with $\Delta \log B_{jt} > 0$ are likely to keep most of their workers regardless of the sign of $\Delta \log A_{jt}$, while those with $\Delta \log B_{jt} < 0$ will tend to lose a lot of workers if $\Delta \log A_{jt} < 0$. Without correcting for endogenous mobility, estimating Equation 18 will result in a biased estimate of $\widehat{\varepsilon_A^W}$, where the bias is

$$\widehat{\varepsilon_A^W} - \varepsilon_A^W = (\alpha - 1)\varepsilon_A^W \frac{\text{Cov}(\Delta \log A_{jt}, \Delta \log B_{jt} | S_{ijt} = 1)}{\text{Var}(\Delta \log A_{jt} | S_{ijt} = 1)} > 0 \tag{21}$$

Since $(\alpha - 1)\varepsilon_A^W < 0$ (firms with high amenities can pay lower wages) and $\Delta \log A_{jt}$ is negatively correlated with $\Delta \log B_{jt}$ in the sample, endogenous mobility will lead to upward biased estimates of the passthrough elasticity.

D.2 Example 2

Take the previous example, but suppose B_j does not vary with time. Instead, assume that the firm's FOC for the wage takes the form

$$\alpha A_{jt} g(W_{jt})^{\alpha-1} = W_{jt} \times \left(\frac{1+\epsilon_W^L}{\epsilon_W^L} \right) \times \phi_{jt}^{-1} \tag{22}$$

where ϕ_{jt} is a time-varying firm-specific wedge between the wage and the MRPL.[41] The passthrough and selection equations are then

$$\Delta \log W_{jt} = \varepsilon_A^W \Delta \log A_{jt} + \varepsilon_A^W \Delta \log \phi_{jt} + \Delta C_t \tag{23}$$

and

$$S_{ijt} = 1 \iff \theta \varepsilon_A^W \Delta \log A_{jt} \geq \tilde{\eta}_{ij}^u - \Delta C_t + \Delta \log I_t - \theta \varepsilon_A^W \Delta \log \phi_{jt} \tag{24}$$

As in Example 1, $\Delta \log \phi_{jt}$ will be negatively correlated with $\Delta \log A_{jt}$ in the sample since both increase the probability of staying. If ϕ_{jt} is unobserved, $\widehat{\varepsilon_A^W}$ will be biased down towards zero, with

$$\widehat{\varepsilon_A^W} - \varepsilon_A^W = \varepsilon_A^W \frac{\text{Cov}(\Delta \log A_{jt}, \Delta \log \phi_{jt} | S_{ijt} = 1)}{\text{Var}(\Delta \log A_{jt} | S_{ijt} = 1)} < 0 \tag{25}$$

since wages are increasing in both productivity and ϕ_{jt}.

D.3 Discussion

As shown, selection bias from endogenous worker mobility arises even in the simplest of logit discrete-choice models of labor supply. In the given examples, the bias could be corrected by estimating the first-stage selection model and obtaining a correction term for the passthrough regression. In the above example, this would involve a logistic regression of S_{ijt} on $\Delta V_{ijt} - \Delta \log I_{it}$. In general, we do not know the underlying labor supply model or DGP, and so we choose to follow the literature in specifying the first stage as a Probit model and use the common correction approach following Heckman (1979).

More complicated models may lead to differences in the resulting selection bias. Note that

[41] Here ϕ_{jt} could represent dynamic constraints or adjustment costs (as in Appendix E.2.2, Chan et al. (2025), Seegmiller (2021), Yeh et al. (2022)), or bargaining/collusion (as in Delabastita and Rubens (2023))

in both examples above, the magnitude of the bias is increasing in ε_A^W. Intuitively, if firms have heterogeneous passthrough elasticity parameters (due perhaps to firm-specific labor supply parameters, θ_j), the resulting selection bias will be greater in magnitude, as high-passthrough firms are even more likely to shed workers, increasing the correlation between the error and change in productivity. This intuition is confirmed in our empirical application, with Table B.5 showing that the bias from endogenous mobility is greater for the workers facing higher passthrough elasticities.

E Simple Models of Passthrough

This appendix presents several simple models of wage setting in imperfect markets and derives the characteristics of the passthrough elasticity for each. Our focus here is to show under what conditions passthrough is fixed vs heterogeneous, and what mechanisms may drive any observed heterogeneity we find in the data. This appendix contains the derivations and results discussed in the "Passthrough Theory" section of the introduction, and provides several extensions of the simple logit model in Appendix D.

E.1 A Simple Model of Labor Demand

Consider a profit-maximizing firm with production function $y = Af(L)$ where $A > 0$ is the firm's idiosyncratic productivity level. Assume that the production function is such that $f(L) > 0$, $f' > 0$, and $f'' < 0$, and that the firm faces a labor supply curve given by

$$L^s = g(W),$$

where $g(W)$ is twice continuously differentiable with $g(W) > 0$, $g' > 0$. Here W is the real wage per unit of labor. Theorem 1 shows that under very general conditions, an increase in A generates an increase in W, that is, there is positive passthrough from firms' shocks to wages.

Theorem E.1. *Under the preceding assumptions on A, W, f, and g, the elasticity of workers' wages with respect to firms' productivity shocks is positive, $\frac{dW}{dA}\frac{A}{W} > 0$, if either of the following two conditions holds: (a) $g'' \leq 0$, or (b) $g'' > 0$ and $d\tilde{g}(W)/dW > 0$ with $\tilde{g}(W) \equiv g(W)/g'(W)$.*

Proof. The problem of the firm is given by,

$$\pi = \max_L Af(L) - W(L)L \qquad \text{s.t. } L = g(W).$$

We can plug in the labor supply function to rewrite the problem as

$$\pi = \max_{W} Af(g(W)) - Wg(W).$$

The first order condition with respect to W is given by,

$$\pi'(W) : Af'(g(W))g'(W) - Wg'(W) - g(W) = 0,$$

so we can write

$$\begin{aligned} Af'(g(W))g'(W) &= Wg'(W) + g(W) \\ A &= \frac{Wg'(W) + g(W)}{f'(g(W))g'(W)}, \end{aligned}$$

and in logs

$$\log A = \log(Wg'(W) + g(W)) - \log(f'(g(W))) - \log(g'(W)).$$

Taking derivatives with respect to W we get,

$$d\log A = \frac{g'(W) + Wg''(W) + g'(W)}{Wg'(W) + g(W)} - \frac{f''(g(W))g'(W)}{f'(g(W))} - \frac{g''(W)}{g'(W)}.$$

Hence, we can write

$$\begin{aligned} \frac{d\log A}{d\log W} &= \frac{\frac{g'(W)+Wg''(W)+g'(W)}{Wg'(W)+g(W)} - \frac{f''(g(W))g'(W)}{f'(g(W))} - \frac{g''(W)}{g'(W)}}{\frac{1}{W}} \\ &= W\left(\frac{g'(W) + Wg''(W) + g'(W)}{Wg'(W) + g(W)} - \frac{f''(g(W))g'(W)}{f'(g(W))} - \frac{g''(W)}{g'(W)}\right). \quad (26) \end{aligned}$$

Then, it follows that the elasticity of firms' wages with respect to productivity, $\epsilon_A^w = \frac{d\log W}{d\log A}$, is given by

$$
\begin{aligned}
\epsilon_A^w &= \frac{1}{W\left(\frac{g'(W)+Wg''(W)+g'(W)}{Wg'(W)+g(W)} - \frac{f''(g(W))g'(W)}{f'(g(W))} - \frac{g''(W)}{g'(W)}\right)} \\
&= \left[W\left(\frac{2\left(g'\left(W\right)\right)^2 - g\left(W\right)g''\left(W\right)}{\left(\left(Wg'\left(W\right)+g\left(W\right)\right)g'\left(W\right)\right)} - \frac{f''\left(g\left(W\right)\right)g'\left(W\right)}{f'\left(g\left(W\right)\right)}\right)\right]^{-1}. \qquad (27)
\end{aligned}
$$

Notice that the second term in the brackets is negative and the denominator of the first term is positive since $f' > 0, f'' < 0$, and $g' > 0$. A sufficient condition for our result to hold is that the numerator of the first term in brackets is positive. If $g''(W) \leq 0$, then this condition is trivially satisfied. If $g'' > 0$, a sufficient condition is that $d\tilde{g}(W)/dW > 0$. To see that this is the case, notice that

$$
\tilde{g}'\left(W\right) = \left[\left(g'\left(W\right)\right)^2 - g\left(W\right)g''\left(W\right)\right] / \left(g'\left(W\right)\right)^2,
$$

which implies that

$$
\begin{aligned}
\tilde{g}'\left(W\right) > 0 &\implies \left(g'\left(W\right)\right)^2 - g\left(W\right)g''\left(W\right) > 0 \\
&\implies 2\left(g'\left(W\right)\right)^2 - g\left(W\right)g''\left(W\right) > 0 \\
&\implies \epsilon_A^w > 0,
\end{aligned}
$$

which gives us our result.

E.2 A Micro-founded Model of Labor Market Power

The framework set up in this section acts as the baseline model for the following sections. Assume that a labor market is populated by N workers and J firms. Each firm operates a simple revenue production function $Y_j = AL_j^\alpha$ where $A_j > 0$ represents firm-specific revenue shifters (such as productivity or demand shocks), and $\alpha \in (0, 1)$ determines returns to scale in labor. Workers can choose to work for any firm j or choose non-employment. Working for firm j provides utility $V_{ij} = \theta \log W_j + \log B_j + \eta_{ij}^u$ where $W_j > 0$ is the wage paid to workers at firm j, $B_j > 0$ is an exogenous non-pecuniary benefit provided to all workers at the firm, and η^u_{ij} is the (unobserved to the firm) individual utility gained by worker i at firm j. We will assume that utility is increasing in the (log) wage such that $\theta > 0$. The outside option provides utility $V_{i0} = \theta \log W_0 + \log B_0 + \eta^u_{i0}$. We assume that η^u_{ij} is i.i.d and follows a type 1 extreme value (Gumbel) distribution. This provides the following expression for the share of workers at firm j:

$$S_j = \frac{B_j W_j^\theta}{B_0 W_0^\theta + \sum_{k \in \mathcal{J}} B_k W_k^\theta}$$

where the number of workers at firm j is $L_j = S_j N$ and $I \equiv B_0 W_0^\theta + \sum_k B_k W_k^\theta$ represents a market-level wage index. The labor supply elasticity which arises from this model for firm j is $\epsilon^L_W = \frac{dS_j N}{dW_j} \frac{W_j}{S_j N} = \theta(1 - S_j)$. Firms in this setting will endogenize both the direct effect of wages on labor supply and the indirect effect of wages on the market wage index.

E.2.1 Log-Linear Labor Supply

Suppose the model is as above, but that firms are atomistic such that $S_j \approx 0$ and firms take the market wage index I as exogenous. This corresponds to the model in Appendix D.1 where we show that the passthrough elasticity is constant and equal to $\epsilon^W_A = \frac{1}{1+\theta(1-\alpha)}$.

E.2.2 Adjustment Costs

Suppose we restrict the model as in Section D.1, with atomistic firms and a log-linear labor supply curve. Further, assume that firms face linear adjustment costs when hiring and firing labor. In particular, the firms must pay a cost of $\phi_1 > 0$ per worker hired, and a cost of $\phi_2 > 0$ per worker fired. We show that the addition of these adjustment costs leads to positive asymmetric passthrough and a passthrough which is decreasing in firm size and productivity. We suppress firm subscripts for simplicity of notation. Firms solve the following profit maximization problem:

$$\max_W \left\{ Ag(W)^\alpha - Wg(W) - \phi_1(g(W) - L_{-1}) I_{L > L_{-1}} - \phi_2(L_{-1} - g(W)) I_{L \leq L_{-1}} \right\}$$

where L_{-1} is the firm's previous employment level and $I_{L > L_{-1}}$ is an indicator variable which equals 1 if the firm increases its employment relative to its previous employment level and 0 otherwise. Likewise, $I_{L \leq L_{-1}} = 1$ if the firm decreases employment and is 0 otherwise. We first focus on the first case, where the firm increases its employment such that $I_{L > L_{-1}} = 1$ and $I_{L \leq L_{-1}} = 0$. The first order condition for the firm is:

$$\alpha A g(W)^{\alpha-1} = W\left(\frac{1+\theta}{\theta}\right) + \phi_1$$

It is difficult to solve this equation for W, so instead we can plug in the labor supply curve and solve for A

$$A = \frac{1}{\alpha}\left(\tilde{B}W^{\theta}\right)^{1-\alpha}\left(\frac{1+\theta}{\theta}W + \phi_1\right). \tag{28}$$

We are interested in the passthrough elasticity: $\epsilon^w_A = \frac{dW}{dA}\frac{A}{W}$, but it is easier to derive $\frac{1}{\epsilon^w_A} = \frac{dA}{dW}\frac{W}{A}$. We can plug in the expression of A from the previous step and get the following:

$$\frac{1}{\epsilon^w_A} = \frac{dA}{dW}\frac{W}{A} = \frac{W(1+\theta)}{W(1+\theta)+\phi_1\theta} + \theta(1-\alpha).$$

Since this equation is continuous and monotone in wages, we can invert it to obtain the passthrough elasticity for positive changes in employment. Since labor is strictly increasing in productivity, this also means that this is the passthrough elasticity for positive changes in productivity:

$$\epsilon^w_{A+} = \frac{1}{\frac{W_j(1+\theta)}{W_j(1+\theta)+\phi_1\theta} + \theta(1-\alpha)} \text{ if } \Delta A_j > 0, \tag{29}$$

A similar procedure gives us the passthrough elasticity for negative changes in productivity:

$$\epsilon^w_{A-} = \frac{1}{\frac{W_j(1+\theta)}{W_j(1+\theta)-\phi_2\theta} + \theta(1-\alpha)} \text{ if } \Delta A_j < 0. \tag{30}$$

Note that when $\phi_1 = \phi_2 = 0$ both of these elasticities collapse back to the constant and symmetric elasticity from the log-linear case, i.e.: $\epsilon^w_{A+} = \epsilon^w_{A-} = \frac{1}{1+\theta(1-\alpha)}$. If the adjustment costs are not zero, then equations (29) and (30) show that passthrough will depend on wages and thus firm productivity. In particular, we know that for positive hiring and firing costs, we have $\epsilon^w_{A+} > \frac{1}{1+\theta(1-\alpha)} > \epsilon^w_{A-}$, which implies positive asymmetric passthrough for any positive hiring and firing costs.

We then ask whether the passthrough elasticities are increasing or decreasing in the magnitude of the costs. To answer this question, we first consider the hiring cost case (ϵ^w_{A+}):

$$\frac{d\epsilon^w_{A+}}{d\phi_1} = \frac{\theta(\theta+1)\left(W - \phi_1 \frac{dW}{d\phi_1}\right)}{\left((1-\alpha)\theta^2\phi_1 + (\theta+1)((1-\alpha)\theta+1)W\right)^2}$$

where we have taken into account that the optimal wage is an implicit function of the hiring cost parameter. In order to determine the sign of this expression, we need to solve for $\frac{dW}{d\phi_1}$. To do this, note that from the first order conditions (Equation (28)) we know that the wage is an endogenous variable which is a function of exogenous variables $(A, \tilde{B})$ and parameters (α, θ, ϕ_1). Taking derivatives with respect to ϕ_1 on both sides of Equation (28) provides

$$0 = \frac{\tilde{B}^{1-\alpha} W^{\theta(1-\alpha)-1}\left(\frac{dW}{d\phi_1}\left((\alpha-1)\theta^2\phi_1 + (\theta+1)((\alpha-1)\theta-1)W\right) - \theta W\right)}{\alpha\theta}.$$

Solving for $\frac{dW}{d\phi_1}$ gives us

$$\frac{dW}{d\phi_1} = -\frac{\theta W}{(1-\alpha)\theta^2\phi_1 + W(\theta+1)(1+\theta(1-\alpha))} < 0.$$

Thus, equilibrium wages are decreasing in hiring costs. This is intuitive: the more employment increases, the more wages increase. Since increases in hiring costs reduce the equilibrium employment of the firm, we will see lower wages as hiring costs increase. This also means that the passthrough elasticity for positive productivity shocks is strictly increasing in the hiring cost, i.e.: $\frac{d\epsilon^w_{A+}}{d\phi_1} > 0$. A similar exercise shows that the passthrough of negative shocks is strictly decreasing in firing costs, i.e.: $\frac{d\epsilon^w_{A-}}{d\phi_2} < 0$. This confirms the above intuition that passthrough in this model will be positive and positive asymmetric for any linear hiring or firing costs. However note that the passthrough elasticity itself is also decreasing in log productivity $\left(\frac{d\epsilon^w_{A+}}{d\log A} < 0\right)$, meaning that while passthrough for individuals firms will be positive asymmetric, larger and more productive firms will tend to have less passthrough of both positive and negative shocks than smaller firms. To confirm this, observe that

$$\frac{d\epsilon^w_{A+}}{d\log A} = \frac{\theta(\theta+1)W\phi_1(\theta\phi_1 + (1+\theta)W)}{\left((\alpha-1)\theta^2\phi_1 + (\theta+1)W((\alpha-1)\theta-1)\right)^3} < 0$$

which is negative since $\alpha < 1$.

E.2.3 Labor Market Power

Here we return to the general logit demand model in Appendix E.2 above with non-atomistic firms. This framework allows for competitive interaction between firms with varying degrees of labor market power. We include the firm subscript notation in order to differentiate between the wage and labor share of the firm (j) from the outside option (0). The labor supply function for a firm in this market is then

$$g(W_j) = S_j N = \frac{B_j W_j^\theta}{B_0 W_0^\theta + \sum_{k \in \mathcal{J}} B_k W_k^\theta} N$$

where the firm interacts strategically with other firms by endogenizing the effect of wage changes on the market wage index. Taking derivatives of S_j with respect to the wage gives us:

$$\frac{dS_j}{dW_j} = \theta(1 - S_j)\frac{S_j}{W_j}$$

which provides the following expression for the labor supply elasticity:

$$\begin{aligned} \epsilon_W^L = \frac{dg(W_j)}{dW_j}\frac{W_j}{g(W_j)} &= \frac{dS_j}{dW_j} N \frac{W_j}{L_j} \\ &= \theta(1 - S_j). \end{aligned}$$

The firm's problem is the same as in Appendix D.1, giving the same first order condition of

$$\alpha A_j g(W_j)^{\alpha-1} = W_j \times \left(\frac{1 + \epsilon_W^L}{\epsilon_W^L}\right). \tag{31}$$

Note that in this case, the share and labor supply elasticity are all implicit functions of A_j via the wage (i.e.: $S_j(W_j(A_j))$ and $\epsilon_W^L(W_j(A_j))$). We can take the derivative of this expression w.r.t. A_j on both sides to obtain:

$$L^{\alpha-1}\alpha S_j^{\alpha-2}\left(S_j + \frac{dW_j}{dA_j}A_j(\alpha - 1)\frac{dS_j}{dW_j}\right) = \frac{dW_j}{dA_j}\left(1 + \frac{\epsilon_W^L - W_j \frac{d\epsilon_W^L}{dW_j}}{\left(\epsilon_W^L\right)^2}\right).$$

Solving for $\frac{dW_j}{dA_j}$ and multiplying by $\frac{A_j}{W_j}$, we obtain the passthrough elasticity:

$$\epsilon_A^w \equiv \frac{dW_j}{dA_j}\frac{A_j}{W_j} = \frac{A_j}{W_j\left(\frac{N^{1-\alpha}S_j^{1-\alpha}\left(\epsilon_W^L+\left(\epsilon_W^L\right)^2-W_j\frac{d\epsilon_W^L}{dW_j}\right)}{\alpha\left(\epsilon_W^L\right)^2}+A_j(1-\alpha)\frac{dS_j}{dW_j}\frac{1}{S_j}\right)}.$$

By noting that $\frac{d\epsilon_W^L}{dW_j} = -\theta\frac{dS_j}{dW_j}$, using equation (31) to substitute in for A_j, and plugging in the values for $\frac{dS_j}{dW_j}$ and ϵ_W^L, we can obtain an expression for the passthrough elasticity in terms of parameters and the firm's labor market share:

$$\epsilon_A^w = \frac{1+\theta(1-S_j)}{1+\theta(1+(1+\theta(1-S_j))(1-\alpha)(1-S_j))} > 0.$$

Since $S_j \in (0,1)$, we know that the passthrough elasticity in this model is positive. The next question is whether or not the passthrough elasticity is increasing or decreasing in log productivity, A_j. We can take the derivative of the elasticity with respect to $\log A_j$ which, after the same substitution process as above, leads to the following expression:

$$\frac{d\epsilon_A^w}{d\log A_j} = \frac{\theta^2(S_j-1)S_j(\theta(S_j-1)-1)\left(\alpha(\theta(1-S_j)+1)^2-\theta\left(\theta(1-S_j)^2-2S_j+1\right)\right)}{\left(\theta\left(\alpha-(1-\alpha)\theta(1-S_j)^2+S_j(1-\alpha)-2\right)-1\right)^3}.$$

The sign of this expression depends on both labor market parameters and firm characteristics. In particular, $\frac{d\epsilon_A^w}{d\log A_j} > 0$ if and only if $0 < \alpha < \frac{\theta}{1+\theta}$ and $0 < S_j < 1 + \frac{1}{\theta} - \sqrt{\frac{1+\theta}{(1-\alpha)\theta^2}}$. This means that in a labor market with very elastic labor supply (θ sufficiently high relative to α), there is a size cutoff, S^*, where larger firms pass negative productivity shocks on to wages more than positive shocks (negative asymmetric passthrough) while smaller firms pass positive shocks on to wages more than negative shocks (positive asymmetric passthrough). Since firm share is itself strictly increasing in productivity, this implies that the passthrough curve (the relationship between log wages and log productivity) is s-shaped—convex for low A_j and concave for high A_j. The cutoff between "small firm" and "large firm" in this context (the inflection point in the curve) is determined by the ratio of the utility value of log wages θ to the returns to scale parameter α. In markets with fairly inelastic labor ($\theta \to 0$) or close to constant returns to scale ($\alpha \to 1$), that size cutoff goes to zero and all firms will exhibit negative asymmetric passthrough. For example, in the simple case where $\alpha = \theta = 1$, passthrough will be negative asymmetric and decreasing in size/productivity for all firms.

E.2.4 Other Labor Supply Curves

Suppose now the labor supply curve is not log-linear and takes the form $g(W) = B_j W_j^\theta + C_j$ where $C_j < 0$ represents the (negative) amenities or disutility experienced by those employed at firm j. As before we assume B_j, W_j, and θ are all positive and suppress the firm subscripts. This labor supply curve provides the following labor supply elasticity:

$$\epsilon_W^L = \frac{\theta B W^\theta}{B W^\theta + C}.$$

The firm's problem is the same as above. Taking the first order condition (see Equation (16)), and plugging in the values for $g(W)$ and ϵ_W^L, we get

$$BW^\theta \left(-\frac{\alpha A \theta \left(BW^\theta + C \right)^{\alpha - 1}}{W} + \theta + 1 \right) + C = 0. \tag{32}$$

Solving for A gives us

$$A = \frac{W^{1-\theta} \left((\theta + 1) BW^\theta + C \right) \left(BW^\theta + C \right)^{1-\alpha}}{\alpha B \theta}. \tag{33}$$

To obtain the passthrough elasticity, we take derivatives with respect to A on both sides of Equation (32), solve for $\frac{dW}{dA}$ and multiply by $\frac{A}{W}$. This gives us

$$\epsilon_A^w = \frac{dW}{dA} \frac{A}{W} = -\frac{\alpha A \left(BW^\theta + C \right)^{\alpha+1}}{\alpha A \left(BW^\theta + C \right)^\alpha \left(B(\alpha\theta - 1) W^\theta + C(\theta - 1) \right) - (\theta + 1) W \left(BW^\theta + C \right)^2}.$$

We can simplify this by plugging in the expression for A in Equation (33). The passthrough elasticity is then

$$\epsilon_A^w = \frac{1}{1 + \theta(1 - \alpha) - \theta \left(\frac{(1-\alpha)C}{BW^\theta + C} + \frac{C}{(1+\theta)BW^\theta + C} \right)} > 0$$

which, as expected, is positive. Taking derivatives with respect to log productivity gives

$$\frac{d\epsilon_A^w}{d\log A_j} = -\frac{BC\theta^2 W^\theta \left(BW^\theta + C\right)\left(B(\theta+1)W^\theta + C\right)\Theta}{\left(B^2(\theta+1)((\alpha-1)\theta-1)W^{2\theta} + BC((\alpha-1)\theta-2)W^\theta + C^2(\theta-1)\right)^3}$$

with $\Theta \equiv \left(C^2(\alpha-\theta-2) + B^2(\theta+1)((\alpha-1)\theta+\alpha-2)W^{2\theta} + 2(\alpha-2)BC(\theta+1)W^\theta\right)$ which is always positive under the above assumptions and as long as $B_j W_j^\theta + C_j > 0$. Thus, the relationship between log wages and log productivity is convex and passthrough in this model is positive asymmetric.

E.3 Discussion

It is clear that in a simple model of imperfect labor markets, some predictions for passthrough are invariant across specifications ($\epsilon_A^w > 0$) while others depend critically on the nature of the labor supply curve (such as whether passthrough is increasing or decreasing in productivity). However, knowledge of the labor supply curve is not enough to predict passthrough, nor does an estimate of the passthrough elasticity necessarily allow mapping out the labor supply curve. In fact, one can decompose the passthrough elasticity into the component due to the effect of productivity on labor requirements, and the effect of changes in labor requirements on the wage. Formally, the passthrough elasticity can be written as

$$\epsilon_A^w = \frac{dW}{dA}\frac{A}{W} = \frac{dW}{dL}\frac{L}{W}\frac{dL}{dA}\frac{A}{L} = \frac{\epsilon_A^L}{\epsilon_w^L}, \tag{34}$$

where ϵ_A^L is the elasticity of labor demand with respect to firm productivity, and ϵ_w^L is the labor supply elasticity. This implies that the passthrough elasticity is inversely related to the labor supply elasticity, such that (holding ϵ_A^L fixed) firms facing lower labor supply elasticities will have higher passthrough elasticities. This relationship is intuitive: if the labor supply elasticity is infinite, as in a perfectly competitive labor market, the passthrough elasticity will be zero and idiosyncratic firm shocks will have no effect on wages. Given that optimal wages in this setting are given by a markdown from marginal productivity of labor, MPL, such that $W = \mu MPL$ where $\mu = \epsilon_W^L / \left(\epsilon_W^L + 1\right)$, we might expect that firms with greater market power (greater wage markdowns) exhibit higher degrees of passthrough. If larger, more productive firms tend to be on less elastic portions of their labor supply curve, then we should also see larger and more productive firms have larger passthrough elasticities.

However, the passthrough elasticity also depends on the characteristics of the labor demand function, itself a function of both the production and labor supply functions. If the firm's labor demand elasticity, ϵ_A^L, is also decreasing in productivity (as is the case in the market power example above), then we may see either positive or negative asymmetry in passthrough. Given parameter values of $\theta \approx 5$ and $\alpha > 0.9$, passthrough will be always negative asymmetric and decreasing in productivity, and market share because the slope of ϵ_A^L with respect to A_j and S_j is negative and greater in absolute value than the slope of ϵ_W^L.

F Passthrough of Efficiency vs Demand Shocks

The frameworks in the previous sections assume the existence of a well-defined revenue production function which we can treat as equivalent to a price taking firm with a quantity production function. Here we follow Klette and Griliches (1996) and De Loecker (2011) and derive a simple case where this assumption holds. We then show how passthrough of output demand shocks and TFPR may differ from production efficiency shocks (TFPQ).

Suppose a firm faces a downward sloping output demand function, with $Y_j(P^o_j) = D_j(P^o_j)^{-\varepsilon^d}$, where P^o_j is the firm's output price relative to an aggregate price index, ε^d is the price elasticity of demand, and D_j is a firm-level demand shifter. Let the firm's physical production function take the form $Y_j = E_j L_j^{\tilde{\alpha}}$ where E_j is the firm-level efficiency shifter (or TFPQ). Firms are atomistic and face the same log-linear labor supply function as in D.1.

The firm's revenue production function can then be written as

$$R_j = P^o_j Y_j(P^o_j) = (D_j)^{1-\theta^d} Y_j^{\theta^d} = (D_j)^{1-\theta^d} (E_j L_j^{\tilde{\alpha}})^{\theta^d} \tag{35}$$

where $\theta^d \equiv (\varepsilon^d - 1)/\varepsilon^d$. We can thus rewrite the revenue production function as $R_j = A_j L_j^{\alpha}$ where $\alpha = \tilde{\alpha}\theta^d$ is a composite parameter combining the curvature of the production function and demand function, and $A_j = D_j^{1-\theta^d} E_j^{\theta^d}$ is TFPR.

In this setting, passthrough of A_j (TFPR) will be $\epsilon^W_A = \frac{1}{1+\theta(1-\alpha)}$ as before, but passthrough of E_j (TFPQ) will be

$$\epsilon^W_E = \frac{\theta^d}{1 + \theta(1-\alpha)} < \epsilon^W_A, \tag{36}$$

since $\theta^d \leq 1$.

In our empirical setting, we do not observe prices, and so we are implicitly estimating a revenue production function and composite TFPR terms similar to what we derive here. As such, our empirical estimates of passthrough should be seen as an upper bound (when $\theta^d = 1$) of the passthrough of TFPQ shocks.

G Two-sided Fixed Effect Regression

G.1 Identification

In this Appendix, we discuss the identification of the parameters in our model of wages with two-sided fixed effects and time-varying firm characteristics. Recall the model of wages we use is given by

$$w_{ijt} = \alpha_i + X_{it}\Gamma_t + \psi_{j(i,t)t} + \xi_{ijt}, \tag{37}$$

where X_{it} is a matrix of time-varying worker observable characteristics–hence Γ_t is indexed by t. For example, return to college degree may be different in 2000 than in 1990. Heuristically, the identification can be achieved in three parts: the covariate coefficients, the individual fixed effects, and the firm fixed effects.

First, we discuss the identification of the coefficient on the time-varying covariates, Γ_t. Since we also allow firm effects to vary by time, the framing of our identification argument is different from the standard setup in Abowd et al. (1999) and the following literature, but the logic is essentially the same. In our setup, it is most convenient to think of each firm-time pair as a separate firm. This means all workers are "switchers" in that they face different (but perhaps common) firm effects each period. Identification proceeds then using "common switchers", defined as workers who work in the same firm as each other in two consecutive periods. Denote by C_t the set of common switchers between $t-1$ and t so that we have $(i,m) \in C_t$ if $f(i,t) = f(m,t)$ and $f(i,t-1) = f(m,t-1)$, where i and m are workers, and $f(i,t)$ denotes the firm where worker i works in period t. Consider the difference in wages of two workers i and m, who work in firm j in period t and firm k in period $t-1$,

$$w_{ijt} - w_{mjt} = \alpha_i - \alpha_m + (X_{it} - X_{mt})\Gamma_t + \xi_{ijt} - \xi_{mjt}$$
$$w_{ikt-1} - w_{mkt-1} = \alpha_i - \alpha_m + (X_{it-1} - X_{mt-1})\Gamma_{t-1} + \xi_{ikt-1} - \xi_{mkt-1}$$

Subtracting the second equation from the first equation on both sides, we get

$$\Delta w_{ijt} - \Delta w_{mjt} = (X_{it} - X_{mt})\Gamma_t - (X_{it-1} - X_{mt-1})\Gamma_{t-1} + \Delta\xi_{ijt} - \Delta\xi_{mjt}$$

Identification of the (time-varying) coefficients on the time-varying covariates (Γ_t for all t) is thus obtained from the common switcher wage growth differentials.[42]

Second, we discuss the identification of the firm-time effects. The firm-time effects for firm j at time t and firm k at $t-1$ can be written as:[43]

$$\begin{aligned}\psi_{j(i,t)t} =& \mathbb{E}_i\Big[w_{ijt} - \alpha_i - X_{it}\Gamma_t - \xi_{ijt} \;\Big|\; f(i,t) = j\Big] \\ =& \mathbb{E}_i\Big[w_{ijt} - \alpha_i - X_{it}\Gamma_t \;\Big|\; f(i,t) = j\Big] \\ \psi_{k(i,t-1)t-1} =& \mathbb{E}_i\Big[w_{ikt-1} - \alpha_i - X_{it-1}\Gamma_{t-1} - \xi_{ikt-1} \;\Big|\; f(i,t-1) = k\Big] \\ =& \mathbb{E}_i\Big[w_{ikt-1} - \alpha_i - X_{it-1}\Gamma_{t-1} \;\Big|\; f(i,t-1) = k\Big],\end{aligned}$$

where the second and fourth line use $\mathbb{E}\left[\xi_{ijt}|f(i,t)=j\right] = 0$.[44] Then, we can write the difference of the firm-by-time fixed effects for individual i that switches from firm k to j

$$\psi_{j(i,t)t} - \psi_{k(i,t-1)t-1} = \mathbb{E}_i\Big[w_{ijt} - w_{ikt-1} - X_{it}\Gamma_t + X_{it-1}\Gamma_{t-1}\Big| f(i,t) = j \;\&\; f(i,t-1) = k\Big]$$

Since all covariates are identified and w and X are given by the data, we can identify all firm-time fixed effects using switchers– i.e. $\big((i, k(i,t-1), t-1) \to (i, j(i,t), t)\big)$–wages and observable characteristics, with a normalization of one firm-time fixed effect. Recall that all workers in our setup are considered *switchers* since each firm has a different fixed effect in each period.

Finally, we discuss the identification of the time-invariant worker effects. Worker i's fixed effect can be written as:

$$\begin{aligned}\alpha_i =& \mathbb{E}_{j(i,t)t}\Big[w_{ijt} - \psi_{j(i,t)t} - X_{it}\Gamma_t - \xi_{ijt}\Big] \\ =& \mathbb{E}_{j(i,t)t}\Big[w_{ijt} - \psi_{j(i,t)t} - X_{it}\Gamma_t\Big].\end{aligned}$$

Notice that we do not rely on having multiple jobs per worker-year pair for our identifica-

[42] Note that it doesn't matter what firms worker i and m had worked at in $t-1$ and in t. As long as they are common switchers their firm-time fixed effects will cancel each other out.

[43] j and k can be the same firm or different firms.

[44] The full identification assumption on ξ_{ijt} is that $\mathbb{E}\left[\xi_{ijt}|\alpha_i, \psi_{j(i,t)t}, X_{it}\right] = 0$

tion. However, having multiple job information available helps us to get better estimates as it increases the effective number of switchers. To see that this is the case, assume that individual i worked at firms j and k in period t. We then have:

$$w_{ijt} - w_{ikt} = \psi_{j(i,t)t} - \psi_{k(i,t)t} + \xi_{ijt} - \xi_{ikt}$$

so we can get

$$\begin{aligned}\psi_{j(i,t)t} - \psi_{k(i,t)t} =& \mathbb{E}\Big[w_{ijt} - w_{ikt} + \xi_{ijt} - \xi_{ikt}\Big| f(i,t) = j \;\&\; f(i,t) = k\Big] \\ =& \mathbb{E}_i\Big[w_{ijt} - w_{ikt}\Big| f(i,t) = j \;\&\; f(i,t) = k\Big]\end{aligned}$$

Considering that in our sample more than 50% of workers held at least two jobs during a year, including the additional job observations allows for better identification of the firm-by-time fixed effects, increases the number of switchers per firm, and thus mitigates the extent of the limited mobility bias (Andrews et al., 2008).

G.2 Results

In this section, we use the estimates derived from our statistical model of wages to study the characteristics of the distribution of log hourly wages. First, we consider the standard decomposition of the variance of log hourly wages, which is given by,

$$Var\left(w_{ijt}\right) = \underbrace{Var\left(\alpha_i + X_{it}\Gamma_t\right)}_{\text{Worker Component}} + \underbrace{Var\left(\psi_{j(i,t)t}\right)}_{\text{Firm Component}} + \underbrace{2 \times Cov\left(\alpha_i + X_{it}\Gamma_t, \psi_{j(i,t)t}\right)}_{\text{Wage Sorting Component}} + \underbrace{Var\left(\xi_{ijt}\right)}_{\text{Residual}},$$

where the first and second components capture the fraction of the variance of log hourly wages accounted for by heterogeneity across workers and firms. The third component accounts for the variation in log earnings that can be attributed to the sorting of workers to firms, that is, how much of the variation in wages is due to the fact that high quality workers–as measured by $\alpha_i + X_{it}\Gamma_t$—are hired by high-wage firms—as measured by $\psi_{j(i,t)t}$.

Table G.1 presents the results of our wage decomposition exercise and analyzes the effects of limited mobility bias in our estimates. The baseline results using the full pooled sample across all years available in our data is shown in column 1. We find that around 51% of the variance in log hourly wages is accounted for by variations in workers' characteristics while 11.3% is accounted for by variations in firm-by-time characteristics. Our estimates also show that sorting, as measured by the covariance between the worker and firm fixed effects, does not account for much of the variation in hourly wages (only 1%). Our estimates are somewhat different than other studies that implement the AKM estimator and typically find that workers' characteristics account for at least 60% of the total dispersion in labor earnings (as in Lamadon et al. (2022) and (Sorkin, 2018)) whereas firms' characteristics account for less than 10% of the variation in labor income (as in Lamadon et al. (2022) and Song et al. (2019)). One reason our results differ is that we use hourly wages in our estimation, while the other papers generally use annual income which conflates variation in hours with variation in wages. We discuss this in more detail below.

One concern as mentioned above is that estimates from such specifications may suffer from limited mobility bias due to firms (or firm-times in our case) which are weakly connected to the rest of the largest connected set. We explore the degree to which this may be the case by successively removing firm-time observations with low numbers of connections and estimating the parameters of our wage model with a restricted connected set. Specifically, we start by using the full sample of workers and firms from 1991 to 2010 to characterize the graph of connections between them. We then obtain for each firm-time pair the number of (ex-ante connections) in this graph and drop any firm-times with a number of connections below a minimum threshold—shown in the top row of Table G.1.

We then recalculate the largest connected set and estimate our model on the corresponding subset of firms and workers. Columns 2 through 8 of Table G.1 show the results from this procedure. Comparing the results from the full sample with no restrictions (column 1) to the most restricted sample where we drop all firm-time observations with less than 100 connections before re-estimating the connected set and fixed-effect model shows (column 8) that there is little to no bias in our full sample results. In particular, removing firms with few connections does not affect substantially our estimates of the variation in worker characteristics or the correlation between firm and worker effects. These measures remain relatively constant across our increasingly restrictive samples. As such, we use our baseline

Table G.1 – Contribution of Workers Characteristics, Firms' Characteristics, and Sorting

	Minimum number of ex-ante connections:								
Min # Connections:	1	2	3	4	5	10	15	50	100
Share Explained by:									
$\alpha_i + X_{it}\Gamma_t$	51.0%	51.0%	51.1%	51.3%	51.4%	52.1%	52.7%	54.4%	55.4%
$\psi_{(i,t)j}$	11.3%	11.0%	10.3%	10.0%	9.5%	8.4%	7.9%	6.8%	6.4%
$2 \times Cov\left(\psi_{(i,t)j}, \alpha_i + X_{it}\Gamma_t\right)$	1.0%	1.0%	1.3%	1.4%	1.5%	1.6%	1.6%	1.2%	1.1%
$Corr\left(\psi_{(i,t)j}, \alpha_i + X_{it}\Gamma_t\right)$	0.02	0.02	0.03	0.03	0.03	0.04	0.04	0.03	0.03
Num $i \times j \times t$ obs.	57,509,434								
Unique firms	450,467								
Unique firm/times	2,967,450								
Unique Workers	4,329,825								
Largest Connected set contains:									
Firm/times	2,784,546	2,639,123	2,258,122	2,043,546	1,800,386	1,196,300	871,560	257,752	116,421
% of baseline sample	(93.8%)	(89.0%)	(76.1%)	(68.9%)	(60.7%)	(40.3%)	(29.4%)	(8.7%)	(3.9%)
Workers	4,303,394	4,299,071	4,290,456	4,281,289	4,271,422	4,219,321	4,169,563	3,931,396	3,755,195
% of the sample	(99.4%)	(99.3%)	(99.1%)	(98.9%)	(98.7%)	(97.4%)	(96.3%)	(90.8%)	(86.7%)
Firms	412,822	389,135	349,627	313,090	281,466	188,705	138,320	39,909	17,532
$i \times j \times t$ observations	57,295,638	57,130,540	56,666,144	56,308,219	55,812,613	53,721,761	51,828,097	44,116,870	39,491,246
Mean hourly wage	5.17	5.17	5.17	5.17	5.17	5.18	5.19	5.2	5.21
Variance of hourly wage	0.30	0.30	0.30	0.30	0.30	0.29	0.29	0.26	0.25
R^2	0.63	0.63	0.63	0.63	0.62	0.62	0.62	0.62	0.63
RMSE	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.33	0.32
% of Firms in connected set:									
¡=2 connections	35.1%	14.8%	4.0%	2.30%	1.40%	0.55%	0.35%	0.04%	0.00%
¡5 connections	39%	31.90%	21.90%	15.60%	7.90%	1.80%	1.10%	0.14%	0.00%
¡10 connections	57.00%	54.70%	47.30%	42.20%	35.10%	13.00%	5.80%	0.80%	0.20%
Mean connections	42.0	44.2	51.2	56.1	62.9	89.9	117.8	325.6	632.1
Median connections	8	8	10	12	14	21	29	81	166

Notes: Table G.1 presents the results of our wage decomposition exercise and analyzes the effects of limited mobility bias in our estimates. Specifically, it shows how the contribution of workers' characteristics, firms' characteristics and sorting varies at different minimum thresholds of number of ex-ante connections. Our procedure is to use the full sample to characterize the graph of connections between workers and firms. We then obtain for each firm-time pair the number of (ex-ante connections) in this graph and drop any firm-times that have fewer than the minimum number of connections listed in the top row of each column. We then recalculate the largest connected set and estimate our model on that subset of firms and workers. All estimates are obtained by pooling data from 1991 to 2010.

Table G.2 – Decomposition of the Variance of log Wages

specification	Wage measure	Firm Effects	Time period	% α	% ψ	%r	% $cov(\alpha,\psi)$
1 (baseline)	hourly	time-varying	1991-2010	51	11	37	1
2	hourly	fixed	1991-2010	49	10	39	1
3	annual	time-varying	1991-2010	59	10	30	1
4	hourly	time-varying	1996-2000	66	7	28	-1
5	hourly	time-varying	2000-2004	65	9	27	-1
6	annual	time-varying	1996-2000	70	6	23	1
7	annual	fixed	1991-2010	54	10	30	3
8	annual	fixed	1996-2000	65	14	22	0

Notes: Rows 1 to 8 show of Table G.2 the results of the wage variance decomposition from 8 different specifications. Row 1 shows our baseline results in the paper. Column two specifies the wage measure used in the decomposition, Column three indicates whether or not the firm effects vary by time. Column four shows the data time period used in the analysis. Columns five to eight show the decomposition effect. α represents person effects, ψ represents firm effects, $cov(\alpha,\psi)$ shows the covariance between worker and firm effects, r represents the residual. The numbers in each row may not add up to exactly 100 due to rounding.

full-sample estimates going forward, confident that they do not suffer from limited mobility bias.

Finally, we explore what drives the differences between our results and the literature using AKM-style regressions. There are three key aspects of our approach which differentiate it from most of the previous literature. First, we allow the firm effect to vary over time (by year). Second, we decompose hourly wages rather than annual income. Third, we estimate the model over a comparatively long panel (20 years). We repeat our wage decomposition exercise with various combinations of these differences and report the results in Table G.2. Specification 1 is the same as our baseline in Column 1 of Table G.1. Imposing firm effects that are fixed over time (specification 2) slightly reduces the contribution of the individual effect to the variance of log earnings from 51% to 49%, while using annual income rather than hourly wages (specification 3) increases it to 59%. Imposing both (specification 7) results in 54% of variance from the individual effect. Using shorter panels (specifications 4 to 6, and 8) also increases the share of variance attributed to workers. Overall, the use of a longer panel and hourly wages are roughly equally responsible for the low share of variance being attributed to the individual effect (relative to the literature), while our use of time-varying firm effects plays little to no role in these differences.