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. Our findings are consistent with models of labor market power and suggest a larger role for firm shocks in determining workers' wage variability relative to previous estimates.

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 significant existing literature which 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 account for worker mobility, we firstly exploit independent variation derived from workers' household linkages. In particular, we estimate workers' probability of staying at a firm as a function of their own and their employer's characteristics, as well as 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 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 that move between firms (i.e., switchers). We find that considering endogenous worker mobility greatly changes the impact of idiosyncratic firm shocks, specially if these shocks are negative.

We further deviate from the literature by leveraging the firm- and worker-level infor-

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

mation available in our data to estimate firm-level Total Factor Productivity (TFP) non-parametrically while allowing for arbitrary labor supply and adjustment cost functions. This framework, developed in Chan *et al.* (2023), 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. This is in contrast to most of the previous literature, which generally takes a highly parametric structural or reduced-form approach to estimating passthrough.

Our main empirical analysis consists of a series of worker-level panel regressions that relate log hourly wage growth for stayers with 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 annual earnings of $1,075 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 in productivity. Quantitatively, a one-standard-deviation increase in productivity 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). Workers are more exposed to negative than to positive changes in firm productivity.

Third, accounting for workers' endogenous mobility plays an important role in measuring the impact of firms' shocks on workers' wages. We show that selection in-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.

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)).[2] 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 for young and recently hired workers. Finally, we find that during recessions, the passthrough from positive productivity shocks collapses—becoming essentially zero—whereas the passthrough from negative shocks remains almost unaltered.

Last, we focus on workers that switch firms between periods, and we find that negative firm productivity shocks increase a worker's probability of leaving a firm and switching to another employer, whereas positive productivity shocks have little effect on outward worker mobility. 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 method of self-insurance against negative income shocks. We also find, as predicted by standard job-ladder models, that workers who move from low- to high-productivity firms experience a significant increase in hourly wages, with larger gains associated with greater jumps in the firm productivity distribution. Quantitatively, workers who experience a 10% increase in hourly wages move, on average, to firms with 18% higher productivity than their previous employer, whereas 50% hourly wage gains are associated with a move to a 47% more productive firm on average. Interestingly, when we divide switchers by wage growth percentiles, the average switcher in every percentile of the wage growth distribution is moving

[2] We derive consistent theoretical predictions from several simple models of labor market power in Appendix E)

from a firm with declining productivity to a firm with growing productivity, suggesting that even workers who move down the firm productivity ladder are moving towards firms with higher productivity growth rates.

Passthrough Theory. How much do firms pass productivity shocks to workers wages? The answer to this question depends crucially on the economic environment. In a model with perfectly competitive labor markets where firms are price takers, passthrough will be zero. 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 which 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.[3]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.

[3]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, that the passthrough elasticity is decreasing in firm market share and is negative asymmetric, which is consistent with our empirical findings.

Another key implication of aforementioned imperfect market model is that estimation of passthrough will be complicated by a selection bias problem. For example, the main passthrough mechanism in the model presented in the appendix (absent adjustment costs) arises from firms who have received productivity shocks choosing to move up or down their labor supply curve by changing the wage offered in the labor market. Attempts to estimate this relationship using worker-level data on wages and productivity changes generated by this model will be complicated by the fact that data on wage and productivity changes will under-sample firms which shed workers after a negative productivity shock. Since firms (and thus workers) with larger firm-level passthrough elasticities are more likely to be under-sampled (as they will tend to shed more workers for a given negative shock), this will result in selection bias. This bias will lead to underestimates of the average passthrough of negative shocks relative to positive shocks, which is exactly what we find, and control for, in our empirical strategy.

Related Literature. Our paper relates to literature that studies the relationship between firm shocks and worker earnings. Guiso, Pistaferri and Schivardi (2005) 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 methodology has been implemented for several countries, including the United States, delivering surprisingly similar results. [4]

More recently, several papers have used quasi-experiments to identify shocks to firms and how these are passed to workers' wages. For instance, Kline *et al.* (2019) study rent sharing among innovative firms that receive patent approvals. Similarly, Howell and Brown (2020) use cash windfalls received by firms from government grants as a measure of shocks. Carvalho *et al.* (2022) uses procurement auctions in Brazil as proxies of demand shocks. These quasi-experimental approaches largely identifies passthrough from positive revenue shocks for a select subset of firms. In comparison, our methodology allows us to provide (to

[4] Several recent papers study the empirical and theoretical relation between firms' shocks and workers' wages. See for instance, Berger *et al.* (2022); Souchier (2022), 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), Souchier (2022), among others.

our knowledge the first) estimates of passthrough for both positive and negative TFP shocks across the entire private sector controlling for endogenous worker mobility and unobserved worker quality.

We differentiate from these papers, and the subsequent literature in four ways. First, we measure TFP shocks and control for unobserved worker quality using a dynamic structural model of firm production building on the framework developed in Chan *et al.* (2023). Hence, the passthrough elasticities we recover 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.[5] Second, we estimate how passthrough differs for positive and negative shocks to the firm, finding significant negative asymmetry. [6]Third, by using hourly wages, we isolate the impact of firm shocks on wages separately from hours worked. Fourth, we use detailed administrative data on family linkages to control for the endogenous selection of workers in response to firm shocks and directly estimate passthrough for both incumbent and transitioning workers.[7] We find average passthrough coefficients that are in line with other estimates in the literature, though our passthrough estimates for negative shocks are significantly larger once we account for workers' mobility.

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 effect approach similar to Abowd, Kramarz and Margolis (1999) and Bagger, Christensen and Mortensen (2014).

The rest of the paper proceeds as follows. In Section 2, we introduce our data sources

[5]Using an instrumental variable or quasi-experimental approach to obtain an unbiased estimate of the passthrough from (potentially residualized) revenues or value-added to wages without knowledge of the production function does not solve this endogeneity issue, as even the true passthrough from value-added to wages tells you little about the underlying passthrough from TFP to wages. See Chan *et al.* (2023) for further discussion and evidence.

[6]Ours is not the first paper to study how passthrough varies by the sign of the shock. Juhn *et al.* (2018) study the passthrough from (residualized) firm revenue changes to workers annual earnings. In contrast to this paper, they do not account for the endogenous mobility of workers and find little to no asymmetry in passthrough.

[7]In contemporaneous work, Friedrich *et al.* (2021) also control for endogenous selection and worker mobility while estimating passthrough elasticities. Their approach leverages municipality and time fixed effects as instruments for mobility, whereas our approach leverages detailed individual-level variation on family status and shocks affecting working spouses.

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 D. 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 at 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 crucial when estimating the first stage of the selection model described in Section 3.3. 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 Danish kroner (about 4,600 US dollars in 2010) so as to maintain workers with a high labor-market attachment. These restrictions leave us with 8.98 million worker-year observations for our primary analysis.[8]

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.[9] The key firm-level variables we use are annual revenue (sum of revenue from sales, capital gains, other operating income, and changes in inventories), value added (revenues minus the value of intermediate inputs), 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 which have less than three years of data or are less then three years old since the TFP estimation procedure requires three sequential observations to recover productivity. This leaves us with around 45,000 firms per year, most of which have been in operation for at least 10 years. Table A.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)—has generated a resilient labor market with high turnover, that keeps unemployment spells short even during periods of economic distress (Andersen, 2021).[10] 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

[8]To avoid the disclosure of any 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. All our results have been reviewed to avoid any disclosure of sensitive information.

[9]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.

[10]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's Business Dynamics Statistics data.

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 USA) makes it a relevant economy to study the relation between firm productivity and worker wages.[11]

3 Empirical Strategy

Our approach to estimating passthrough from firm-level productivity to worker-level wages builds on the framework developed in Chan *et al.* (2023) (CMSX hereafter). Our empirical approach is consistent with theirs, with the exception that estimating passthrough at the worker level additionally requires correcting for endogenous mobility. In this section, we briefly outline the CMSX framework and how we apply it in our setting, focusing on how this paper innovates relative to the literature. We then discuss our approach to estimating worker-level passthrough and how we take into account workers' endogenous mobility and correct for the associated selection bias.

3.1 Theoretical Setting

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. Firms are price takers in output and non-labor input markets, and face uncertainty about future productivity. A key advantage of this framework is that it 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.[12]

[11] 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 1.30 between 1987 to 2008. The Great Recession, generated a significant increase in inequality, with a P90/P10 increasing up to 1.55 in 2009 followed by a further increase to 1.65 in 2017. A significant fraction of this raise in inequality is due a widening of the P90/P50 labor earnings ratio.

[12] See CMSX for details, derivations, proofs and further discussion.

3.2 TFP Estimation

We follow CMSX in measuring firm-level productivity shocks building on the flexible estimation method proposed by Gandhi *et al.* (2020) (GNR hereafter). This 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 input quality from variation in firm productivity .

The main challenge in this step in 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.[13]

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

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

where 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 $\omega_{jt} = \mathbb{E}[\omega_{jt}|\omega_{jt-1}] + \eta_{jt}$, where η_{jt} is an i.i.d. shock to the persistent component of firm's productivity, and ε_{jt} is an i.i.d. ex-post transitory shock that is uncorrelated with adjustments in inputs. In what follows, we use the terms persistent shock and transitory shock to refer to η_{jt} and ϵ_{jt}, respectively.

[13]Ideally, we also want to avoid making any parametric assumptions about the shape of the production function, such as assuming it is Cobb-Douglas or CES, as this implicitly assumes a particular relationship between productivity and input demand which would potentially bias our estimates of the passthrough elasticity. This is especially important when we want to examine asymmetry and heterogeneity in the relationship between the productivity and wages across firms and workers characteristics.

To identify these shocks, we follow CMSX and GNR in imposing standard assumptions on firm decision timing and information sets.[14] 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 following the strategy outlined in GNR. 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).[15] 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 cost functions.[16]

Measuring Labor Input. The most straightforward approach to measure 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 productivity (ν_{jt}). Similarly, changes in the quality of a particular firm's workforce over time, possibly driven by productivity shocks, will also be interpreted as changes in ν_{jt}.[17]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)). This approach, however, implicitly assumes that wages

[14]In particular, we assume that capital, K_{jt}, is a "predetermined" input that is fixed in period t, and that intermediate materials, M_{jt}, is a flexible input chosen every period. We depart from GNR in 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. The timing of the model is such that firms enter period t knowing K_{jt}, L_{jt-1},and ω_{jt-1}. They then observe $\eta_{j,t}$ and choose L_{jt}, M_{jt}, and K_{jt+1}. After the input decisions are set, the firm observes ϵ_{jt}. We assume that firms can adjust wages in response to both shocks, but that firms are price-takers in output markets and the market for materials. Our assumption on labor inputs and wages requires us to instrument for labor when estimating the production function. We do so using lags of labor and wages. Other than this change in second-stage instruments, our production function estimation approach follows the procedure outlined in GNR.

[15]Because we do not observe output prices for the firms in our sample, our measure of productivity is "revenue" TFP rather than "quantity" TFP. This implies that variation in measured TFP may contain variation in production efficiency as well as in output demand (Syverson, 2011).

[16]Our approach generally requires that the labor supply and adjustment cost functions faced by the firm are common to all workers within the firm, though they may differ across firms and depend on the distribution of worker characteristics within the firm. We also require that both functions be differentiable. See CMSX for more discussion.

[17]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.

are correlated with worker ability, and that labor markets are competitive conditional on ability, neither of which are appropriate in our context. [18] In particular, if labor markets are perfectly competitive, we should not expect any passthrough from firms' *idiosyncratic* shocks to wages.

In this paper, we follow CMSX in using data on hourly wages, individual characteristics, and employers to estimate the productive ability of each worker with a two-way fixed effect regression similar in style to Abowd *et al.* (1999). In particular, we assume that workers are characterized by time-varying ability $A_{ijt} = A_i \times \Lambda_t(X_{it})$ where A_i is the worker's unobserved time-invariant ability and $\Lambda_t(X_{it})$ is a time-varying function Λ_t 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 the assumption above that the firm faces a single labor supply curve, imply that each firm j pays all workers the same wage conditional on ability. Namely, worker hourly wages (in logs) take the form $w_{ijt} = a_{it} + \lambda_t(X_{it}) + \psi_{jt}$ 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} is a set of worker observable characteristics that are allowed to change over time (i.e., experience, tenure and position within the firm, occupation, education, and age), $\psi_{j(i,t)t}$ 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 uncorrelated to worker or firm characteristics. Here we are also assuming that $\Lambda_t(X_{it})$ is log-linear in X_{it}. In this way, 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

[18] Moreover, several papers use the method first introduced by Abowd *et al.* (1999) to decompose the variance of log wages. Typically, these papers find that around 10% of the dispersion of workers' wages is accounted for by fixed differences across firms. See for instance Barth *et al.* (2016), Song *et al.* (2019), and Engbom and Moser (2022).

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 potential changes in the returns to education, occupation, or position within the firm. Using this specification, we net out the effect of firm productivity changes on the wage bill and control for observable and unobservable heterogeneity across workers while remaining agnostic about the labor market conditions that induce the distribution of wages we observe in the data.

The estimated value of the individual fixed effect and observable characteristics, denoted by $\hat{\alpha}_i + X_{it}\hat{\Gamma}_t$, is a measure of worker "quality".[19] Importantly, this measure of worker quality is independent from (but potentially correlated with) the characteristics of the firm that employs the worker (which are captured by a firm-time effect $\psi_{j(i,t)t}$).[20] Using this 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. Using these estimates, our ability-adjusted measure of firm productivity comes from estimating the production function in equation 1 where $\ell_{jt} = \log L_{jt}$. Note that the estimation procedure allows ℓ_{jt} to be correlated with productivity ν_{jt} via η_{jt} and ω_{jt-1} but not with ϵ_{jt}.

Appendix Table A.3 shows cross-sectional moments of the distribution of log wage growth, TFP growth, and TFP shocks estimated using our approach.[21]

[19] Appendix F describes in additional detail how we estimate the parameters in Equation 2. Similarly to other results in the literature, we find that about 50% of the variance of w_{ijt} is accounted for worker characteristics $\left(\hat{\alpha}_i + X_{it}\hat{\Gamma}_t\right)$, 11% is accounted for by firm time-varying characteristics, whereas the rest is accounted for by the residual. These results are shown in Appendix Table A.7. In the same table, we discuss the potential bias arising from the lack of mobility of workers across firms (Andrews *et al.*, 2008).

[20] These characteristics include firm-specific labor supply elasticities and adjustment costs. See CMSX for an explicit derivation of the firm wage in this setting.

[21] Our estimates of the production function 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 the service sector, while most estimates of productivity (including GNR) are restricted to manufacturing.

3.3 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 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 (e.g., lagged productivity, firm size, firm age, industry, and so on) and worker characteristics (e.g., ability, gender, age, position and tenure in the firm, wage level, and so on), respectively, δ_t is a time fixed effect that controls for aggregate fluctuations in the economy, and ζ_{ijt} is the residual. The coefficient on x_{jt}, β^x, is our measure of the passthrough elasticity. If the relationship between firm productivity and worker wages is heterogeneous across firms and time (i.e., β^x_{jt}) then β^x will be an estimate of the mean passthrough elasticity across workers in the sample. In the following sections, we will consider several different measures of x_{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 that maintain a stable employment relationship with their firm, which we refer 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 in order 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. Therefore, focusing only on those workers who stay—and thus, are less likely to be at a high passthrough firm experiencing a wage cut—will bias our estimates toward zero, thereby understating the degree of passthrough from firm shocks to wages.[22]

In order to correct for 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 $Pr(D_{ijt} = 1) = \Phi(U\zeta)$, where $D_{ijt} = 1$ if worker i remains at firm j and U is a vector of worker and firm observable characteristics. Since we observe both 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 $\hat{\zeta}$ and then computing the inverse Mills ratio, denoted by $\hat{\lambda}$, which we include in our main regressions. Our identification strategy relies on including observable variation in U which determines the probability that workers will stay or leave their firm, but does not affect the elasticity of workers' wages relative to firm productivity should they choose to stay at the firm in that period.

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 marriage status, separation, change of spouse, and whether or not the individual's spouse is working if married. 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,

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

where x_{jt}, X_{it}, and Z_{ijt} are as above, T_{it} is the set of marital status indicators, E_{it} is an indicator that equals 1 if the worker's spouse is employed, and S_{it} is a vector of observables for the spouse and the spouse's firm, as described above. The indicator function $\mathbb{I}_{x_{jt}}$ captures the asymmetric impact of positive and negative TFP shocks to the firm on the probability

[22]This approach differs from CMSX, who do not consider selection as their analysis is done at the firm-level and so is free of bias from endogenous worker mobility.

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.[23] This requires that 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. This is consistent with 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.* (2021).[24]

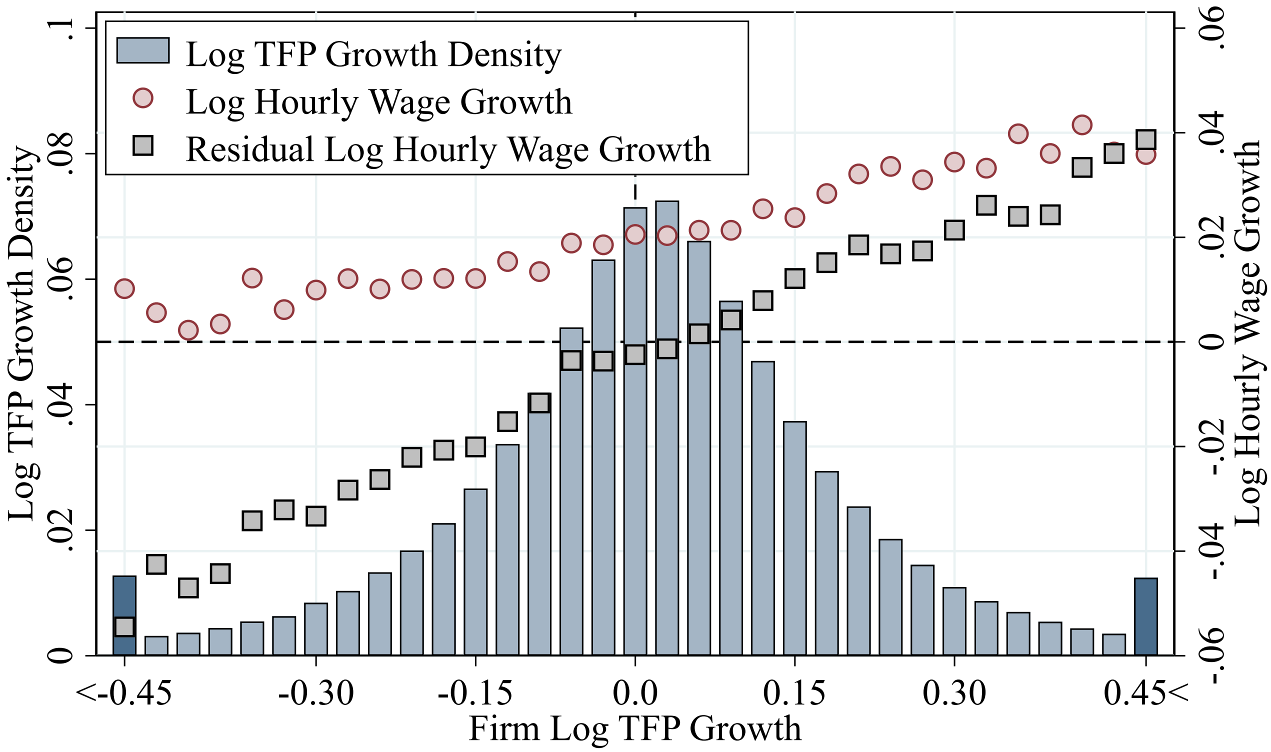
The estimation results of Equation (4)—shown in Appendix Table A.2—indicate that positive productivity shocks increase a worker's probability of staying at the firm, whereas negative shocks do the opposite.[25] We also find that that men, older workers, and workers who have recently changed spouses are more likely to leave a firm, while being married, having a longer tenure in the firm, having a spouse who stays at their firm, and having a spouse who works in a firm experiencing a positive TFP shock, increase the probability of staying. From the estimates of Equation (4), we obtain the inverse Mills ratio which we use in the following section.

[23]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 both periods. We also control for hours and work position in the main second stage passthrough regression.

[24]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.

[25]We also use a linear probability model similar to Equation (4) to calculate the average (conditional) probability of a worker switching jobs within bins of the TFP growth distribution, residualized by the same worker and firm characteristics as Equation (4). The results, shown in Figure A.4, indicate a monotonic decline in the share of workers who separate from their firms as we move from negative to positive firm-level productivity shocks (right y-axis). In particular, the share of workers employed in firms that experience a negative change in productivity of 45 log points is 4 times higher than for firms that receive a 30 log points decline, who are in turn twice as likely to separate as those in firms with 15 log point declines.

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



Note: Figure 1 is based on a pooled sample of firms and workers between the years 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 workers-year and 0.57 million firms-years observations. To construct the plot, we separate firms into 41 equally spaced bins between -.45 and 45. To avoid the disclosure of any sensitive information, the left- and right-most 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 3.3 (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), especially when firms experience a positive change in productivity, but appears to be insulated from negative changes in firm productivity. In fact, average hourly wage growth is positive across the entire TFP growth distribution (all of the red circles are above zero) even for firms experiencing large negative changes in productivity. This would suggest that hourly wages are subject to downward rigidity and that, although there is some passthrough from productivity to wages, it is small and mostly due to positive shocks to productivity.

Second, when we control for worker's 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 decrease 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 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. [26]

Baseline Regression Results

Our main passthrough estimates are based on a series of worker-panel regressions that relate the change in workers' hourly wages to firms' idiosyncratic productivity shocks.[27] More

[26] Furthermore, we find that selection affects the passthrough from firm shocks across the entire distribution of hourly wage growth. As we show in Figure A.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 6% increase in wages. After controlling for selection, we find that 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 3%.

[27] Appendix Table A.3 shows selected statistics for the main variables we use in our analysis. In our sample, the standard deviation of log wage growth for stayers is 0.18 (column 1), which is half of the dispersion in wage growth for switchers (column 2). By comparison, Kurmann and McEntarfer (2019) report an interquartile range of 11 log points (13 log points in our sample). In terms of firms' productivity, we find a standard deviation of the (worker-weighted) persistent component of firms' productivity shocks equal to 0.27. This is larger than other estimates in the literature. For instance, Guiso and Pistaferri (2020) report a standard deviation of firms' persistent shocks of 0.05. Our average passthrough estimates are quite in line with the rest of the empirical literature, indicating that in our sample, firms provide a larger degree of insurance.

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 total log TFP for firm j between periods t and $t-1$. We also include the estimated inverse Mills ratio, $\hat{\lambda}_{ijt}$, obtained from the first-stage estimates of Equation (4). As we just discussed, controlling for selection has important implications for the value of β^{ν}, our main parameter of interest, which measures the average passthrough elasticity from changes in firm productivity to wages.

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 for the average full-time worker in Denmark (see the bottom panel of Table I) or about about 1.8% of the average annual income.[28] Given that in a typical year around 20% of firms in our sample (which employ around 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 fluctuations in workers' income.

We then analyze the passthrough of positive and negative productivity changes to wages separately. We do so by interacting $\Delta\nu_{jt}$ with an indicator function, $\mathbb{I}_{\Delta\nu_{jt}<0}$, that is equal to one if the corresponding productivity change is negative, as in the following specification:

$$\Delta\hat{w}_{ijt} = \beta_0 + \beta_p^{\nu}\Delta\nu_{jt} + \beta_n^{\nu}\Delta\nu_{jt} \times \mathbb{I}_{\Delta\nu_{jt}<0} + Z_{jt}\Gamma_t + X_{jt}\Omega_t + \rho\hat{\lambda}_{ijt} + \delta_t + \zeta_{ijt}, \tag{6}$$

where β_p^{ν} measures the average passthrough from a positive change in ν_{ijt}, whereas $\beta_p^{\nu} + \beta_n^{\nu}$ is the average passthrough from a negative change in ν_{ijt}. The results are shown in column (2) of Table I. First, notice that the coefficient for a positive change is smaller than the

[28]For this calculation, we multiply the value of β^{ν} times the standard deviation of firm productivity growth times the average annual wage of the workers in the corresponding sample. In what follows, we express the impact in terms of 2010 US dollars.

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 and equal to 0.11.[29] This indicates that a one standard deviation change in 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 corresponds with the predictions of our simple model where firms have market power and operate with nearly constant returns to scale.

Transitory and Persistent Shocks

We now turn to analyzing the impact of transitory and persistent 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 first 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 al.* (2018) and Guiso and Pistaferri (2020) for recent reviews).[30] Here, we reevaluate the role of persistent and transitory shocks by including in our baseline specification the persistent and

[29] 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 on their paper). The main difference between our results and theirs comes from controlling for workers' endogenous mobility. In fact, as indicated by column (6) in table I, not controlling for mobility flips the sign of the asymmetry, in that positive shocks have a larger impact on workers' wages than negative shocks (compare 0.062 versus 0.03, the sum of 0.062 and -0.032).

[30] One notable exception is Howell and Brown (2020), who find that a transitory cash flow shock to the firm significantly impacts workers' wages. The transitory shocks we study, however, differ from theirs in that a transitory cash flow can imply a persistent change in productivity if it leads to innovation, the purchase of new equipment, or the incorporation of new technologies.

Table I – The Passthrough from Firm TFP shocks to Wages is Positive and Asymmetric

	Change in Log Hourly Wages, $\Delta\hat{w}_{i,j,t}$										
	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}			.077	.061			.033	.044	.056	.014	.025
			(.007)	(.004)			(.004)	(.004)	(.004)	(.032)	(.007)
$\eta_{jt} < 0$				.070				−.022	.080	.127	.002
				(.007)				(.009)	(.007)	(.041)	(.002)
ϵ_{jt}			.034	.025			.034	.032	.025	.032	.057
			(.003)	(.005)			(.003)	(.004)	(.006)	(.008)	(.010)
$\epsilon_{jt} < 0$				.018				.007	.021	−.007	−.018
				(.008)				(.009)	(.009)	(.018)	(.018)
$\hat{\lambda}_{it}$	−.219	−.278	−.188	−.262					−.230	−.333	−.012
	(.014)	(.015)	(.023)	(.013)					(.020)	(.035)	(.003)
R^2	.78	.78	.79	.79	.78	.78	.78	.78	.81	.44	.70
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}			$873				$386				
$\eta_{jt} > 0$				$689				$504	$638	$167	$2,099
$\eta_{jt} < 0$				$1,495				$252	$1,528	$1,662	$1,914
ϵ_{jt}			$336				$353				
$\epsilon_{jt} < 0$				$252				$319	$252	$336	$554
$\epsilon_{jt} > 0$				$436				$386	$453	$269	$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 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. All monetary values are in 2010 US dollars. Robust standard errors in parentheses are clustered at the firm-level.

transitory components of firm productivity estimated in Section 3.2. We estimate

$$\Delta \hat{w}_{ijt} = \beta_0 + \beta^{\eta}\eta_{jt} + \beta^{\varepsilon}\epsilon_{jt} + Z_{jt}\Gamma_t + X_{it}\Omega_t + \rho\hat{\lambda}_{ijt} + \delta_t + \zeta_{ijt}, \tag{7}$$

where β^{η} and β^{ϵ} are the elasticity of wages with respect to the persistent and transitory components of firms' TFP, respectively.[31] Column (3) of Table I shows the results. We find that although transitory and persistent shocks have a significant impact on hourly wages, wages are more than twice as responsive to persistent than to transitory productivity shocks.

We then separate the impact of transitory and persistent shocks into their positive and negative parts, as we do for TFP growth in Equation (6). 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 worker's annual labor earnings of \$1,495, whereas an increase in η_{jt} of the same magnitude generates an increase of \$689. 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.

Bias and Asymmetry. The evidence presented in 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 the sign of the firm shock. Intuitively, workers in firms with larger passthrough elasticities (and thus face 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. Consistent with this expectation, the estimated coefficients on the inverse mills ratio ($\hat{\lambda}_{ijt}$) in columns (1) to (4) of Table I are

[31] 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 estimate $\hat{\lambda}_{ijt}$ from a separate first-stage regression on η_{jt} and ϵ_{jt} rather than $\Delta\nu_{jt}$.

negative and significant.

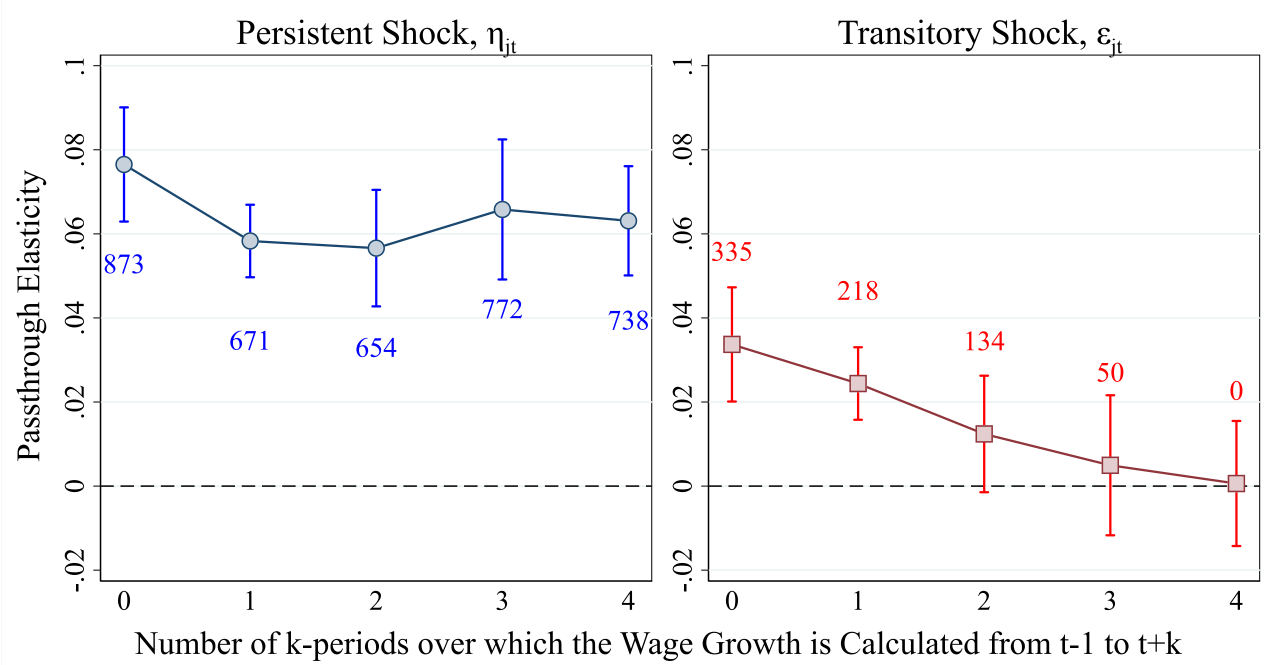
To evaluate the extent of the bias, we repeat the previous analysis without correcting for worker selection induced by endogenous mobility decisions (i.e., we exclude $\hat{\lambda}_{ijt}$ from our regressions). The results are shown in columns (5) to (8) of Table I. As expected, we find that selection biases the estimated coefficient of firms' shocks on hourly wages toward zero. Moreover, the bias is more significant for persistent than for transitory shocks. To see this, compare columns (3) and (7), where the elasticity to persistent shocks declines by more than a half for persistent shocks when we do not control for selection, but remains the same for transitory shocks.[32] Consistent with the intuition above, the passthrough estimates for negative shocks are the most affected by selection: if we ignore selection, we would conclude that negative persistent shocks have a passthrough elasticity of 0.022, which is six times smaller than our baseline (corrected) estimates. These 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 of the results that follow include selection-correction terms.[33]

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 increase 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 with a change in workers' wages between t and $t-1$), but a smaller passthrough at longer horizons (for instance, a correlation between a shock to firms in period t and a wage change between $t+4$ and $t-1$ closer to 0). To study the persistence of passthrough, we modify our baseline specification in Equation (7) by extending the horizon of the wage change on the left-hand side to $t+k$ periods, 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

[32] This is consistent with the timing of our model of firm productivity, which assumes that inputs (including labor, though not wages) are fixed prior to observing ϵ_{jt}.

[33] In Appendix B, we explore the bias which results from removing each additional step of our empirical 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.

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 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.

and other firm and worker observables.[34]

Figure 2 shows on the y-axis the elasticity of worker wages to a persistent or transitory shock to firm productivity at different horizons. Each point on the figure represents a passthrough coefficient from a separate set of first- and second-stage regressions. In both panels, the x-axis corresponds to the periods over which the wage growth is calculated and the vertical lines are 95% confidence intervals for the corresponding regression coefficient. 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 only a small decay in magnitude. In contrast, short-lived transitory shocks have a smaller and less persistent impact on workers' wages, although the effect does not disappear immediately, generating a small but still significant change in workers' wages, even 2 years after the shock.

[34]Note that our selection correction procedure changes as well, such that we run separate first-stage regressions for each separate time horizon, where the dependent variable in the first stage is an indicator of whether the worker stayed at the firm for all $t-1$ to $t+k$ periods.

Aggregate State Dependence Does the passthrough from idiosyncratic firms' shocks to workers' wages changes during recessions relative to expansions? This could be the case, if for example, a large aggregate economic shock, such as the Great Recession, decreases the workers' value of being unemployed (due to a reduction in vacancy postings).[35] This would lower workers' reservation wages giving firms greater ability to pass negative shocks on to their employees' wages. Similarly, a large negative aggregate shock may tighten credit constraints, and thus reduce firms' ability to insure their workers against negative idiosyncratic productivity shocks, inducing a higher passthrough.

To investigate whether passthrough is state-dependent, we estimate Equation (7) for two non-overlapping periods. The first considers observations from the two years of the Great Recession (2008 and 2009), whereas the second period considers all of the other (expansion) years in our sample. Our results, shown in columns (9) and (10) of Table I, indicate that the passthrough from positive firm shocks to worker wages is state-dependent, whereas the passthrough from negative shocks is not, and remains the same between recession and expansion periods.

To see this, first notice that during expansion years, the passthrough coefficients are quite similar to those obtained in our baseline analysis—compare columns (9) and (4) in Table I. This is not surprising, considering that most of the years in our analysis are expansionary years. Second, recession years show a different pattern, especially for the impact of persistent productivity shocks on wages. In particular, the passthrough from negative shocks remains almost unaltered between recessions and expansions (recall that the impact of a negative shock is given by $\beta_p^\eta + \beta_n^\eta$). In other words, firms that receive a negative idiosyncratic productive shock during a recession reduce the wages of their workers. In contrast, the passthrough from positive shocks collapses, becoming insignificant and almost zero, indicating that firms which received a positive productivity shock during the great recession did not, on average, pass that increase on to their workers.[36]

To summarize, in this section we have shown that idiosyncratic shocks to firms' produc-

[35] Between 2007 and 2009, the GDP of Denmark declined around 7.0%, while the unemployment rate rose by 2.0 percentage points.

[36] Our results are consistent with Grigsby *et al.* (2021) who show that during the Great Recession, the probability of US workers of receiving a (nominal) wage cut increased whereas the probability of receiving a wage increase fell sharply.

tivity have a significant and persistent impact on workers' wages, which depend not only on the nature of the shocks (persistent versus transitory) but also on the sign (positive versus negative).[37] In the following sections, we complement these results in two ways. First, we exploit the richness of our data set to explore how passthrough varies across workers and firms characteristics. Second, we focus on the importance of firms' productivity shocks on workers mobility decision and wages.

5 Heterogeneous Passthrough

As we have shown, the average passthrough from firm shocks to wages is significant and asymmetric. Still, 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 firms' shocks to wages is highly heterogeneous and varies substantially across firm and worker groups. To conserve space, we present equivalent results for the impact of transitory shocks in Appendix A.

5.1 Firm Heterogeneity

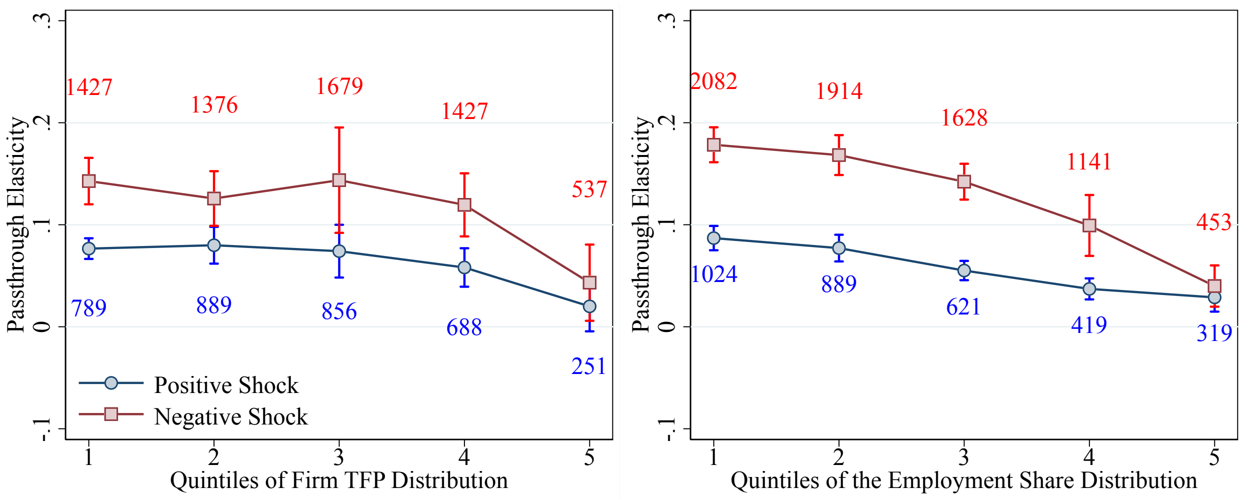
Firm Productivity

We first study whether firms with different productivity levels differ in their level of passthrough. This would be the case if firms have some degree of labor market power such that high productivity firms face a more inelastic labor supply. As the elasticity of the labor supply decreases, greater wage increases are required to obtain the same increase in labor, thereby increasing the measured passthrough. Alternatively, if firms operate with nearly constant returns to scale, larger firms will also be on less elastic portions of their labor demand curve which may decrease passthrough. Our results are consistent with the

[37] In Appendix C we separate productivity shocks into aggregate, industry and idiosyncratic components and show that our results are explained almost entirely by the idiosyncratic firm-level component. We also find that while negative industry shocks are passed on to wages on average, positive industry shocks are not.

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 for quintiles of the labor market share of a firm, where 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.

latter interpretation. Our estimates 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.[38]

We show this by separating our sample of firms into quintiles of their (lagged) log TFP level, ν_{jt-1}. We then assign workers to their corresponding firms in a year and run our baseline specification (Equation 5) separately within each group. Figure 3a shows the results. We find that the passthrough from persistent shocks to firms (both negative and positive) is decreasing in firms' productivity, especially in the top three quintiles of the distribution. For example, workers employed at firms in the lowest productivity quintile gain \$789, or 1.5% in annual income on average when their firm experiences a positive persistent shock of one standard deviation. The impact of negative shocks are even larger, with a \$1,427 drop in annual earnings—or 2.8% of average earnings—after a negative productivity shocks. Workers employed at firms in the highest quintile of the TFP distribution, in contrast, experience much smaller wage changes. On average, these workers gain \$251, or 0.4% in annual income

[38]In this analysis, we controlled for firm size, industry, and other firm- and worker-level characteristics so that we do not confound the effect of these factors with firm productivity,

(lose \$537, or 0.8% in annual income) when their firm receives a one standard deviation positive (negative) persistent shock.

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.[39]

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 \$1,026 from a one standard deviation increase in persistent productivity, and lose \$2,082 after a negative shock of the same magnitude. In contrast, workers employed by firms in the fifth quintile—large firms with around 10% of the employment of their local labor market—are better insured, experiencing gains (losses) of \$319 (\$453) 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.[40]

[39]We calculate employment shares within each industry-municipality, 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. To avoid the disclosure of any sensitive information, we calculate the median share within a quintile as the average share for all firms between the 50 and 51 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.

[40]We find a similar negative relation between passthrough and firm size, as measured by the number of workers. As shown in Figure A.3a, the passthrough elasticity declines from 0.12 for firms of less than 5 workers to basically 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.

5.2 Worker Heterogeneity

Wages and Ability

Workers at different income levels may also be differentially exposed to shocks affecting the firms where they work. Studying how the passthrough varies across the income distribution is important for at least two reasons. First, low-income workers are more likely to be credit constrained. To the extent that idiosyncratic shocks to firms represent an uninsurable risk, finding a higher passthrough for low-income workers might have significant welfare implications, even though the average passthrough is small. Second, variations in the passthrough across income levels might help to explain why individuals at the top and bottom of the income distribution experience larger fluctuations in labor earnings than individuals in the middle of the income distribution (Guvenen *et al.*, 2021). Overall, we find that high-wage and high-ability workers are more exposed to idiosyncratic shocks to firms' productivity than low-wage and low-ability workers.

We start by separating 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 firms' 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 (\$1,763 versus \$285, or 1.9% and 0.8% of the within-group average annual income, respectively) when their firms receive a persistent positive shock to firms' TFP of one standard deviation. This difference is even starker for negative shocks. Workers in the top wage quintile lose \$3,207 in annual labor earnings after such a shock, while those in the bottom quintile lose only \$403.

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, $\hat{a}_{it} = \hat{\alpha}_i + \hat{\Gamma}_t X_{it}$. 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-wage workers experience larger gains and losses than low-wage workers when their firms experience persistent TFP shocks. This is is consistent with the notion that labor earnings for high-income workers such as managers is more linked to firm performance than for low-income workers.[41]

Tenure and Age

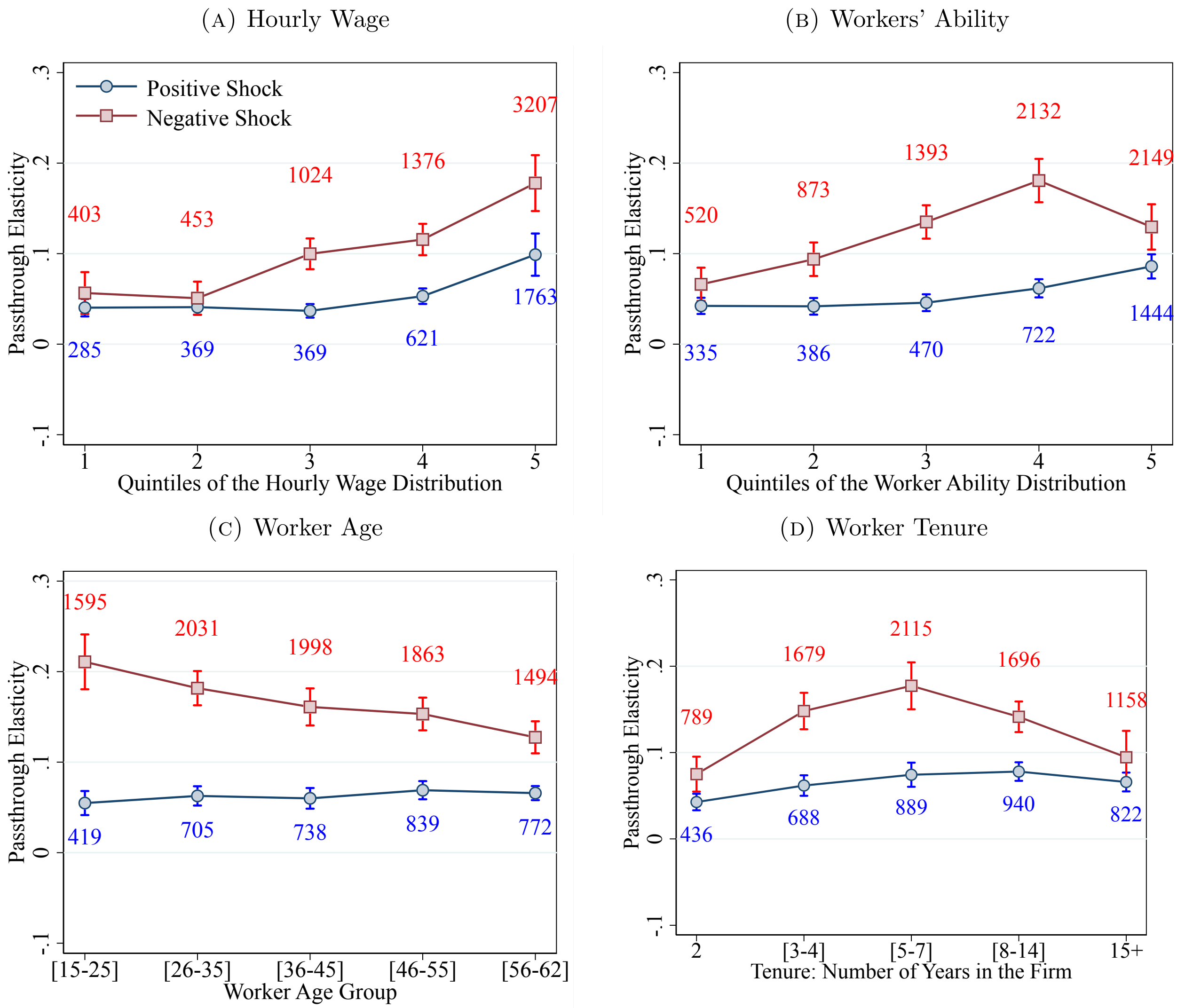
Workers may be more or less exposed to firm shocks, depending on their age and tenure within the firm. For instance, older workers are more likely to have accumulated general work experience, have differing tenure-contingent contracts, or have accumulated specific human capital that is valuable for the firm and difficult to replace. In such cases, the firm may try to insure older and long-tenure workers from negative shocks more than younger or recently-hired workers. 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 (Michelacci and Quadrini, 2009). Our results are consistent with this intuition.

Figure 5c shows the elasticity of wages to a persistent shock to firms' 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's age. This implies that older workers get a higher wage increases 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 (line with squares) is larger than the response to positive shocks and decreases monotonically with workers' age. For instance, workers who are 56 years old or more lose 2.5% of their annual income in response to a one standard deviation negative shock, whereas workers who are between 15 and 25 years old lose 3.4% of their annual income on average.[42]

[41] Consistent with our baseline estimates, the quantitative effect of transitory shocks to TFP is considerably smaller than the effect of persistent shocks (Panel A of Appendix Figure A.2). We do not find statistically significant differences between the passthrough of transitory shocks across the income distribution, although the quantitative impact is larger for workers in the fifth quintile than for workers in the first quintile (compare \$923 to \$285 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 productivity shocks.

[42] 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 A.2). More precisely, for workers who are 25 years old or younger, a negative (positive) transitory shock of one standard deviation translates into a

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 to D present similar statistics for workers in different quantiles of the ability distribution as measured by $\exp(\hat{\alpha}_i + \hat{\Gamma} X_{it})$, the age distribution, and the tenure distribution. 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.

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 4. We find that the passthrough from persistent TFP shocks to wages is hump-shaped in

decrease (increase) of \$370 (\$251) 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 \$604 (\$184) in annual earnings.

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 firms shocks than 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 $2,115 (3.4%) in their annual average income.

6 Switchers

The results of the previous sections focused on the effect of TFP shocks on stayers, that is, workers who maintain a stable employment relationship with a firm for the years over which the change in TFP is calculated. However, a significant fraction of workers switch firms in any given year, potentially in response to shocks to firm productivity. Hence, in this section we shift our focus to those "switchers", defined as workers who change primary employer between two consecutive years.[43] Firm shocks can be passed through to these workers in two ways. First, as we discuss in Section 3.3, productivity shocks are an important determinant of employment risk and job mobility. Second, the wage change which results from this employment change may depend on the productivity level and growth of the firms that worker is moving across. We examine both of these channels in this section.

Workers who switch jobs experience larger income changes than workers than stay in the same job. This difference can be explained, in part, by the fact that switchers are transitioning between firms of (often significantly) different productivity levels.[44] To see this, in Figure 5a, we sort switchers into bins by their log hourly wage growth and plot the (within-bin) average log TFP of their origin and arrival firms. Each red circle in Figure 5 is the average log TFP of the firms which workers of a given wage growth percentile switched out of, while each black square is the average log TFP of the destination firms which workers of the corresponding wage growth percentile switched into.

[43] For workers with multiple jobs in a year, we define the primary employer as the firm that provides the higher income within a year. Our data does not allow us to cleanly distinguish whether an individual passed through an unemployment spell prior to joining a different employer or had a direct transition between employers. Around 20% of workers in our sample change primary employers in any given year.

[44] Appendix Figure A.5 shows that the dispersion in (and average) residual hourly wage growth is higher for switchers than for stayers.

Two patterns are worth noticing. First, the difference in firm productivity between positive and negative wage changes is striking. Workers who experience a reduction in hourly wages of between 25 and 75 log points when they switch firms have moved, on average, to firms that are 10 log points less productive. In contrast, workers who experience an increase in hourly wages of 25 log points have moved to a firm that is on average 25 log points more productive. This difference in productivity increases as workers experience larger wage gains. There is also a group of workers who, despite experiencing a wage cut of between 0 to 20 log points, have moved to firms with greater average productivity, perhaps motivated by prospects of higher future wage growth.[45]

A second noticeable pattern in Figure 5a is that workers experiencing larger wage gains from switching firms are not moving, on average, to firms with higher productivity, relative to workers with smaller, but still positive, wage gains. Instead, workers with larger wage gains tend to be those switching out from relatively low productivity firms. Workers whose log hourly wages increase by 50 log points are switching on average into firms with the same productivity as workers who gain 10 log points in hourly wages, but the former are switching out from firms that are 25 log points less productive.

Interestingly, workers move on average to firms with positive TFP growth, independently of whether the hourly wage growth is positive or negative. Figure 5b plots, for the same wage growth bins, the average TFP growth for switchers' old and new firms. Notably, the average switcher in every bin of the wage growth distribution is moving from a firm with negative productivity growth into a firm with positive productivity growth. This is consistent with standard job ladders models (Burdett and Mortensen, 1998) which predict that workers move from low- to high-productivity firms over time.

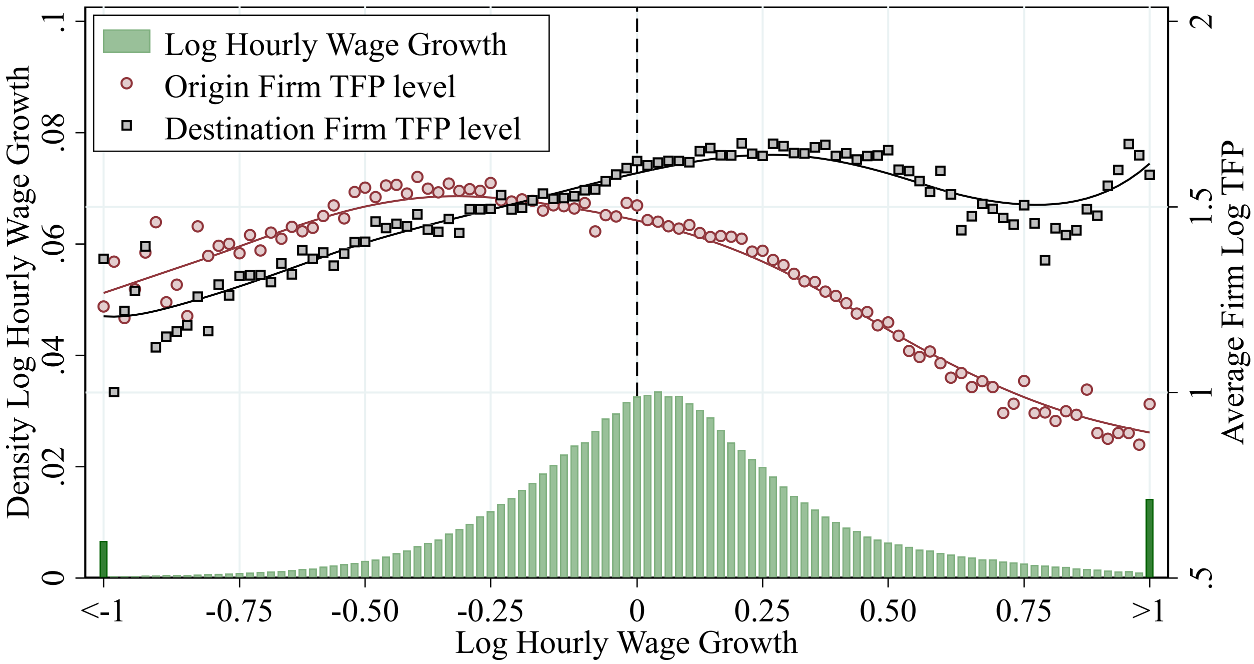
Regression Results

To obtain quantitative estimates of the between-firm passthrough elasticity, we run a set of panel regressions similar to the baseline model we consider in our stayers sample. Notice that the interpretation of a productivity shock is different for switchers than for stayers. For

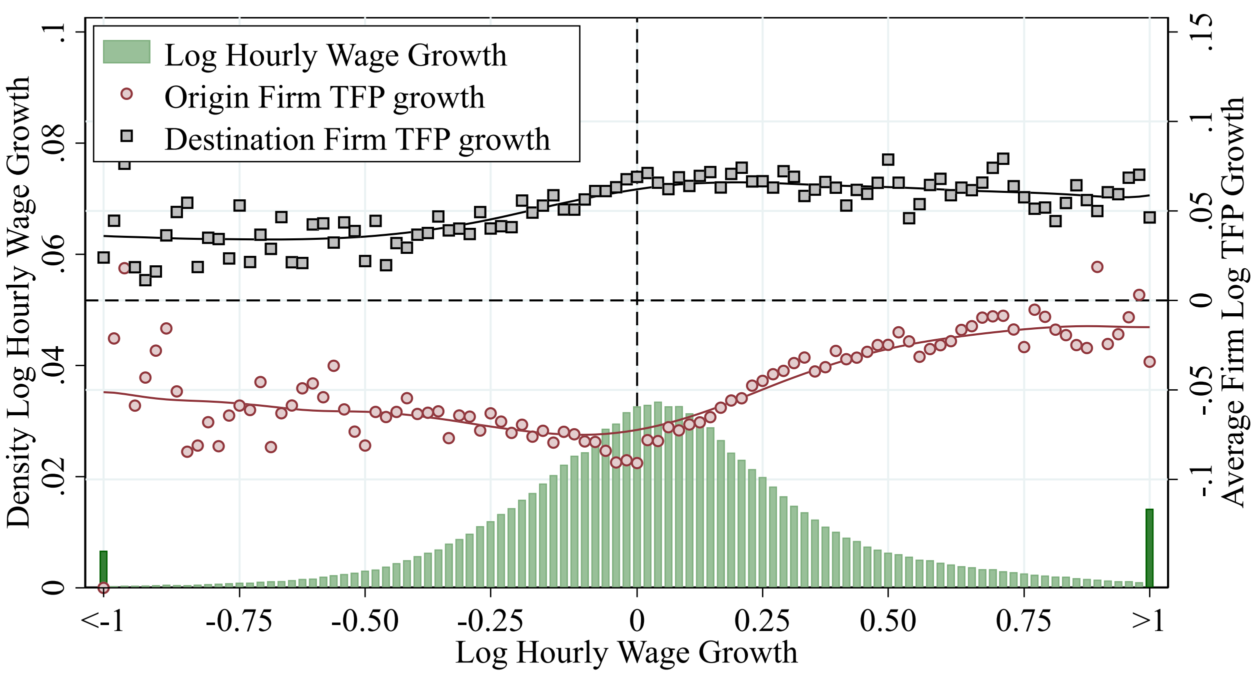
[45]We find similar patterns when looking at different percentiles of the distribution of the log TFP (Figure A.6 in Appendix A). In particular, the higher average productivity of switchers' new firms is not driven by a handful of highly productive firms that are offering higher wages, but rather the productivity distribution of destination firms is shifted to the right.

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

(a) TFP Level



(b) TFP Growth



Note: Figure 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.

stayers, it represents an unanticipated change in productivity in the firm in which they work, whereas for switchers, we define a TFP shock as the unanticipated difference in productivity between two different firms.[46] 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 the worker used to work.

To capture these differences, we modify our baseline specification to include the shocks to the productivity of both of the firms between which the individual is transitioning. In particular, we estimate

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

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. In this case, η_{jkt} is the unanticipated difference in the persistent component of TFP between the old and new firms, defined by $\eta_{jkt} = \omega_{jt} - \mathbb{E}[\omega_{kt}|\omega_{kt-1}]$, whereas 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 lag productivity.[47]

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 (0.131 versus 0.027). 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 \$1,495 versus \$1,914, or 2.5% versus 3.4% of average annual income). One additional remarkable difference with respect to stayers is that the passthrough for switchers is symmetric (the coefficient on $\eta_{jkt} \times \mathbb{I}_{\eta_{jkt}<0}$

[46]The unanticipated change is defined relative to the expected period-t productivity of the origin firm: $\mathbb{E}[\omega_{kt}|\omega_{kt-1}]$.

[47]We control for selection in this regression by including the inverse Mills ratio $\tilde{\lambda}_{ijt}$ which is estimated from a first-stage model similar to Equation (4), with the exception that D_{ijt} is instead an indicator that equals 1 if the worker moved to a different firm in period t.

is effectively 0). This implies that workers climbing up the productivity ladder face similar wage changes as those making equal movements down the ladder.

7 Conclusions

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 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.

Our analysis also offers new insights into how movements up and down the firm productivity ladder affect wages for workers who switch employers. In particular, we show that on average, switchers who obtain larger wage gains are moving out from lower productivity firms than workers who obtain smaller wage gains, but both types of workers move into firms of similar productivity. We also find that switchers are (on average) moving from firms with negative productivity growth to firms with positive productivity growth, regardless of whether they face wage gains or losses. Unlike passthrough for incumbent workers, movements between firms up and down the productivity ladder generates symmetric passthrough from productivity to wages. Taken together, our results suggest an important role for firms' TFP shocks in accounting for workers' wage variability.

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Online Appendix for "Heterogeneous Passthrough from TFP to Wages"

A Additional Tables and Figures

Table A.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

Table A.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 A.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)	
$\Delta\nu_{jt} \times \mathbb{I}_{\Delta\nu_{jt}<0}$	.977***	
	(.004)	
η_{jt}		.313***
		(.006)
$\eta_{jt} \times \mathbb{I}_{\eta_{jt}<0}$		1.111***
		(.004)
Age	-.003***	-.004***
	(.001)	(.001)
Male	-.132***	-.154***
	(.002)	(.002)
Lag Tenure	.040***	.040***
	(.000)	(.000)
Married	.027***	.026***
	(.003)	(.003)
Change Spouse	-.119***	-.119***
	(.011)	(.012)
Spouse's Firm's TFP (ν_{jt})	.017***	.011***
	(.004)	(.004)
Spouse Stayer	.028***	.026***
	(.003)	(.003)
Obs. (Millions)	7.04	7.04

Notes: Table A.2 shows a few selected parameter estimates from our first-stage probit model. $*p < 0.1, **p < 0.05, ***p < 0.01$. Robust standard errors are clustered at the firm-level.

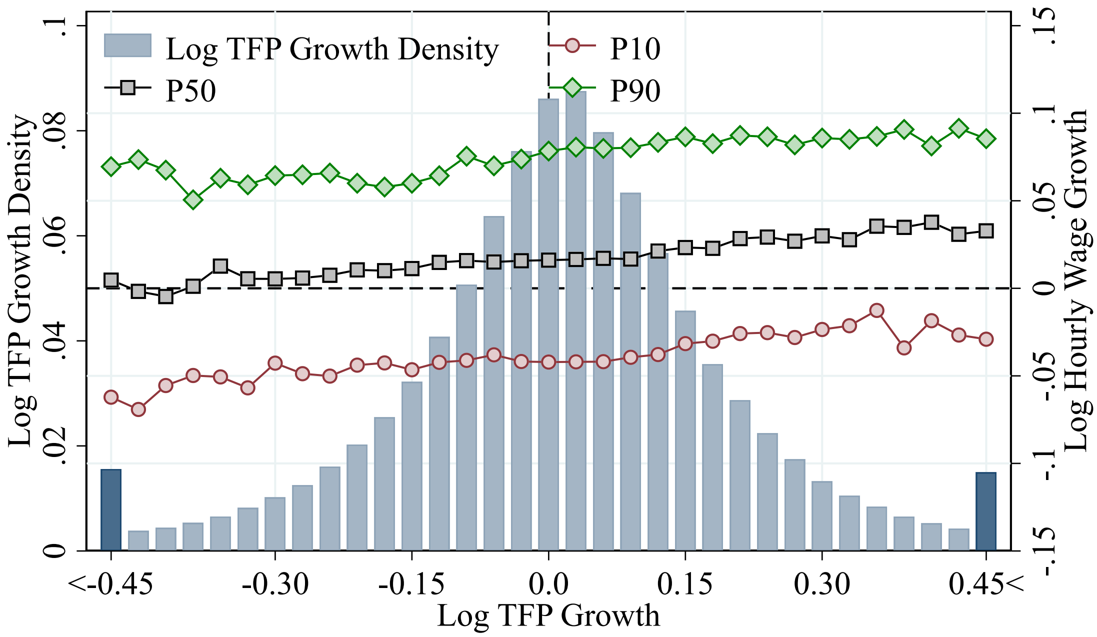
Table A.3 – Summary Statistics for Worker Hourly Wages and Firm Productivity Shocks

	Panel A: Workers		Panel B: Workers			Panel C: Firms		
	Δw_{ijt}		$\Delta \nu_{jt}$	η_j	ϵ_{jt}	$\Delta \nu_{jt}$	η_j	ϵ_{jt}
	Stayers	Switchers		Stayers				
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

Table A.3 shows the sample statistics for workers' log hourly wage growth (Panel A) and firms' productivity shocks (Panel B at the worker-level and Panel C at the firm-level). 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.

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

(a) Hourly Wages



(b) Residual Hourly Wages

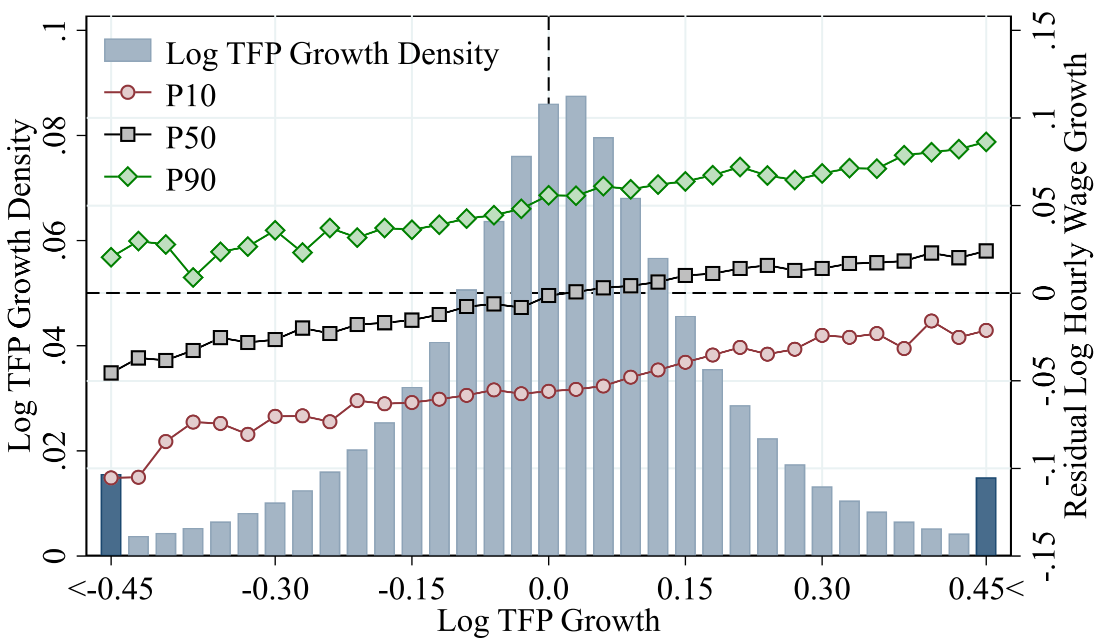
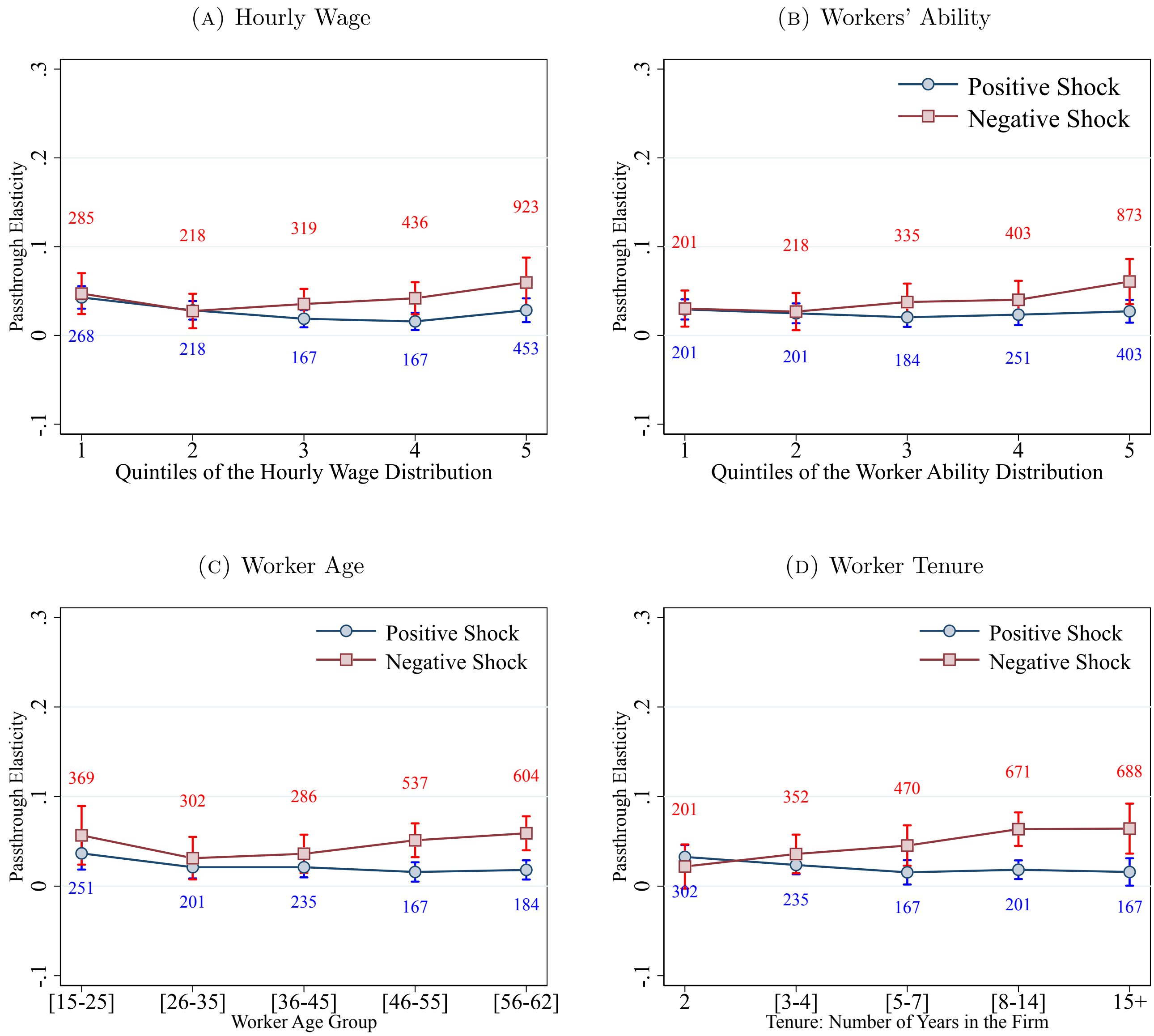


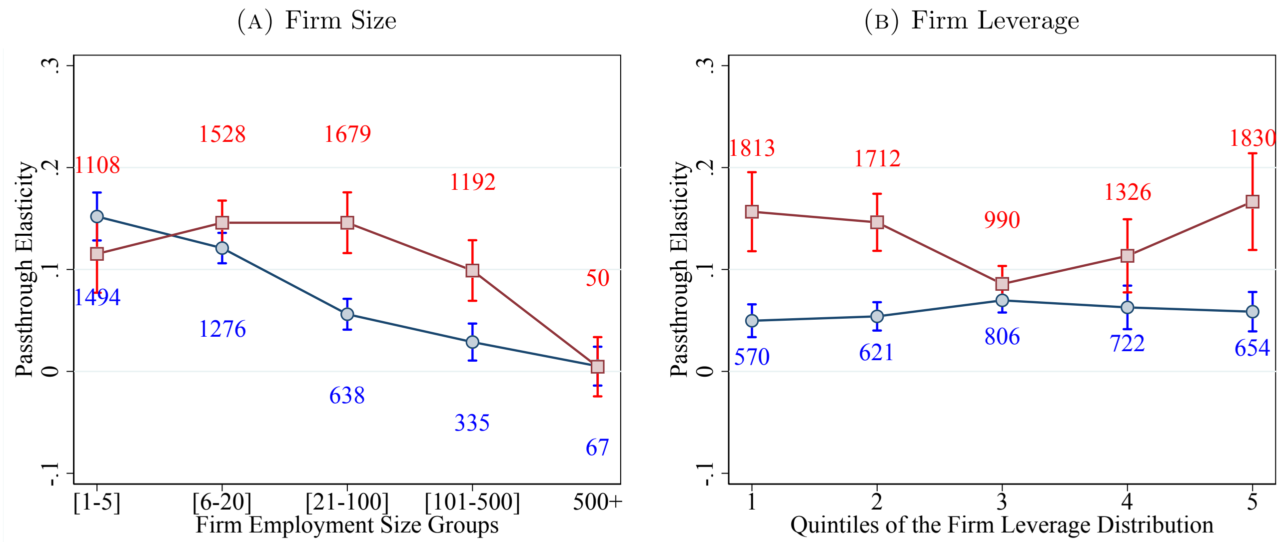
Figure A.1 is based on a pooled sample of firms and workers between the years 1996 to 2010. The blue bars show the share of firms within different bins of the log TFP growth distribution (plotted on the left y-axis). To construct the plot we separate firms into 41 equally sized bins between -.45 and 45. The left- and right-most bins, marked in darker blue, contain the remaining left and right tails of the distribution, and thus are not the same size as the other bins. The right 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 as explained in Section 3.3 (bottom panel). Hourly wage growth measures are calculated for a sample of stayers defined as workers for whom the firm providing the higher total annual earnings was the same in periods t and $t-1$. To avoid disclosure of any sensitive information, we report the mean of all observations within a percentile-band rather than individual observations at the percentile cutoff.

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



Note: Panel A of Figure A.2 shows the elasticity of hourly wages to a persistent (left panel) and transitory (right panel) productivity shock for workers within different age groups. Panel B shows the same statistics for workers within different tenure groups. Tenure is measured as the number of years for which the worker has been employed at that firm. Tenure bins are chosen so as to have groups of roughly similar size.

Figure A.3 – Passthrough is Heterogeneous across Firm Characteristics



Note: Figure A.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 TFP distribution Panel B to D present similar statistics for workers employed in firms of different employment size, labor market share, and firm leverage. 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.

Figure A.4 – Conditional Probability of Switching

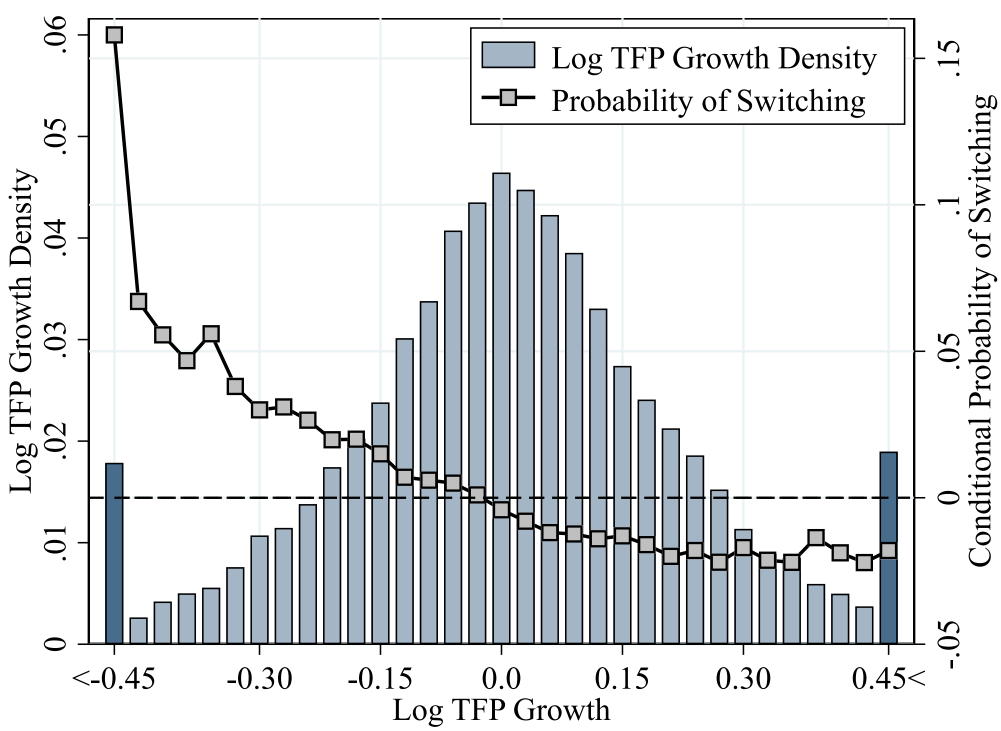
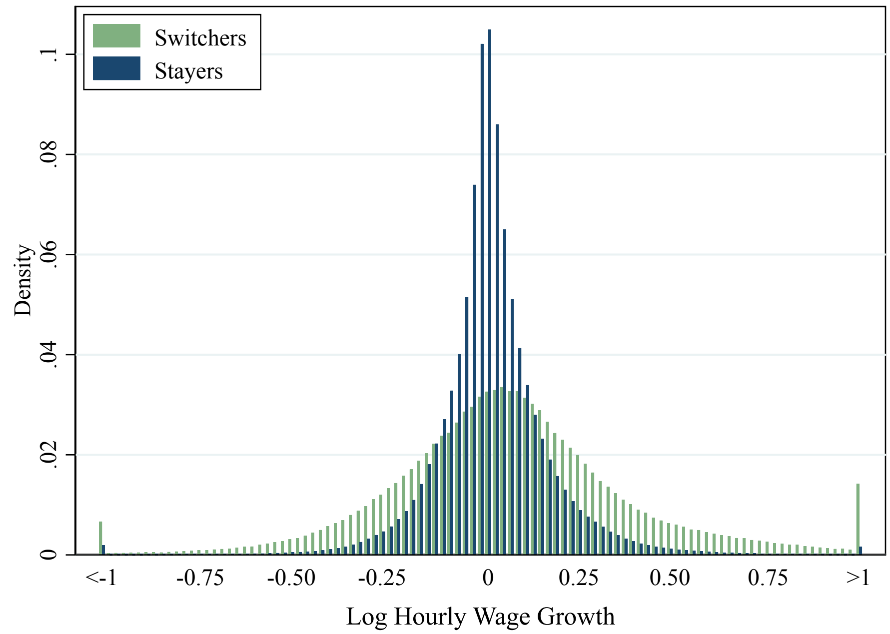


Figure A.4 shows the average conditional switching probability within each bin of the firms' log TFP grow distribution ($\Delta\nu_{jt}$). The conditional probability is obtained from a linear probability model similar to the model used to estimate the inverse Mills ratio. See Section (3.3) for additional details.

Figure A.5 – Log Hourly Wage Growth For Switchers and Stayers



Note: Figure A.5 is based on a pooled sample of stayers and switchers (workers who move across firms between firms $t-1$ and t) and their corresponding firms. In the top panel, the green bars (blue bars) show the share of switchers (stayers) within different bins of the 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, and thus are not the same size as the other bins.

Figure A.6 – Hourly Wage Growth for Switchers and Firm Productivity

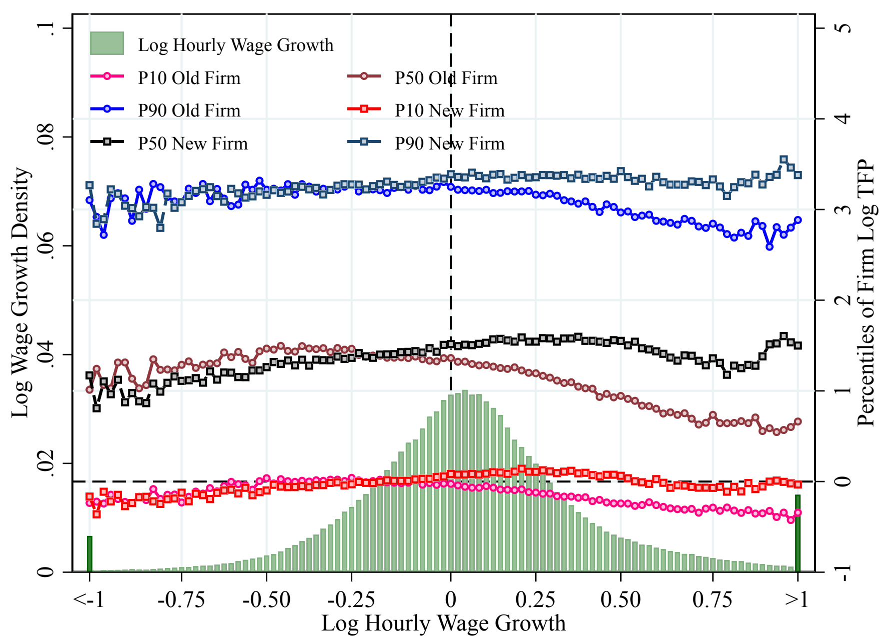


Figure A.6 is based on a pooled sample of switchers (workers who move across firms between firms $t-1$ and t) and their corresponding firms. The green bars show the share of workers within different bins of the hourly wage growth distribution (left y-axis). To construct the graph we partition the wage growth distribution into 101 equally spaced bins between -1 and 1. The left and right-most bins, marked in darker green, encompass the remaining left and right tails of the distribution, and thus are not the same size as the other bins. The circles show percentiles of the log TFP distribution for the firms that employed the workers in period $t-1$; The squares show percentiles of the log TFP distribution for the firms that employed the workers in period t. To avoid disclosure of any sensitive information, we report the mean of all observations within a percentile-band rather than individual observations at the percentile cutoff.

B Alternative Measures of Passthrough

Our empirical approach differs in several different ways to the standard methods used in the rent-sharing literature. In this section, 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 above. As shown in column 1 of Table A.4, 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. the change in annual income could be due to a change in hours worked by the individual, either voluntarily or because of a change in labor demand by the firm).

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 by changes in the log hourly wage (column 3 of Table A.4). 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 slightly less than half is due to changes in hours worked (we find similar results when using our more robust 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

Table A.4 – 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

Table A.4 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 (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 not selection corrected. $*p < 0.1, **p < 0.05, ***p < 0.01$. Robust standard errors are clustered at the firm-level.

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 first that failing to correct for changes in hours will lead to significant over-estimates of passthrough, while not correcting for worker-level ability and mismeasurement of firm shocks will significantly under-estimate passthrough.

C 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

Table A.5 – 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)
$Mills_{it}$	−.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

Table A.5 shows a set of OLS panel regressions controlling for firm and worker characteristics. $*p < 0.1, **p < 0.05, ***p < 0.01$. Robust standard errors are clustered at the firm-level.

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 $\Delta\nu^k_t$), where the residuals are our measure of idiosyncratic firm-level changes in TFP (denoted by $\Delta\nu^f_{jt}$) 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 A.5 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.

D Data and Variable Definitions

In Table A.6, 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 going directly to here (in Danish).

D.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.[48] We construct capital using the permanent 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 * 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 need 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 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

[48]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.

employed for the full year or make more than 150000 DKK in annual income at their primary job.

E Simple Model of Labor Market Power

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.

E.1 A Simple Model of Labor Demand

Consider a profit maximizing firm with production function $y = Af(L)$ where $A > 0$ is the firms' idiosyncratic productivity level. Assume that the production function is such that $f(L) > 0$, $f' > 0$, $f'' < 0$ 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 1. Under the preceding assumptions on A, W, f, and g, the elasticity of workers' wages for 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 $d\phi(W)/dW > 0$ with $\phi(W) \equiv g(W)/g'(W)$.
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

$$\pi = \max_W Af(g(W)) - Wg(W).$$

Table A.6 – 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)
krh,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
aneum, oeeu	Other external expenses

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

$$\begin{aligned} \frac{d\log A}{d\log W} &= \frac{\frac{g'(W)+Wg''(W)+g'(W)}{Wg'(W)+g(W)} - \frac{f''(g(W))g'(W)}{f'(g(W))} - \frac{g''(W)}{g'(W)}}{\frac{1}{W}} \\ &= W\left(\frac{g'(W) + Wg''(W) + g'(W)}{Wg'(W) + g(W)} - \frac{f''(g(W))\, g'(W)}{f'(g(W))} - \frac{g''(W)}{g'(W)}\right). \end{aligned} \tag{8}$$

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

$$\begin{aligned} \epsilon_A^w &= \frac{1}{W\left(\frac{g'(W)+Wg''(W)+g'(W)}{Wg'(W)+g(W)} - \frac{f''(g(W))g'(W)}{f'(g(W))} - \frac{g''(W)}{g'(W)}\right)} \\ &= \left[W\left(\frac{2(g'(W))^2 - g(W)\, g''(W)}{((Wg'(W) + g(W))\, g'(W))} - \frac{f''(g(W))\, g'(W)}{f'(g(W))}\right)\right]^{-1}. \end{aligned} \tag{9}$$

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 $d\phi(W)/dW > 0$. To see that this is the case, notice that

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

which implies that

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

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 $V_{ij} = \theta \log W_j + \log B_j + \eta_{ij}$ 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_{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 $V_{i0} = \theta \log W_0 + \log B_0 + \eta_{j0}$. We assume that η_{ij} follows a type 1 extreme value 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 $\epsilon_W^L = \frac{dS_j N}{dW_j} \frac{W_j}{S_j N} = \theta(1 - S_j)$. 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. The labor supply curve is then $g(W) = \tilde{B}_j W_j^{\theta}$, where $\tilde{B}_j \equiv B_j N/I$ is an exogenous labor supply shifter. To simplify the notation, we dispense with firm subscripts. Firms choose wages to solve the following profit maximization problem:

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

which provides the following first order condition:

$$\alpha A g(W)^{\alpha-1} = W \times \left(\frac{1+\epsilon_W^L}{\epsilon_W^L}\right). \tag{10}$$

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 (10) 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

$$\epsilon_A^w = \frac{dW}{dA}\frac{A}{W} = \frac{1}{1+\theta(1-\alpha)} \tag{11}$$

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

E.2.2 Adjustment Costs

Suppose the model is as above, 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. The following section shows that the addition of these adjustment costs leads to positive asymmetric passthrough and a passthrough which is decreasing in firm size and productivity. As above 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

$$A = \frac{1}{\alpha}\left(\tilde{B}W^{\theta}\right)^{1-\alpha}\left(\frac{1+\theta}{\theta}W + \phi_1\right). \tag{12}$$

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:

$$\epsilon^w_{A+} = \frac{1}{\frac{W_j(1+\theta)}{W_j(1+\theta)+\phi_1\theta} + \theta(1-\alpha)} \text{ if } \Delta A_j > 0, \tag{13}$$

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

$$\epsilon^w_{A-} = \frac{1}{\frac{W_j(1+\theta)}{W_j(1+\theta)-\phi_2\theta} + \theta(1-\alpha)} \text{ if } \Delta A_j < 0. \tag{14}$$

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 (13) and (14) 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 (12)) 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 (12) 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 $\left(\frac{d\epsilon^w_{A+}}{dlogA} < 0\right)$, 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

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

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:

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

The firm's problem is the same as in appendix E.2.1, giving the same first order condition of

$$\alpha A_j g(W_j)^{\alpha-1} = W_j \times \left(\frac{1+\epsilon^L_W}{\epsilon^L_W}\right). \tag{15}$$

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 $\epsilon^L_W(W_j(A_j))$). We can take the derivative of this expression w.r.t. A_j on both sides to obtain:

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

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 (15) 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

Finally, suppose 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 dis-utility 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 (10)), and plugging in the values for $g(W)$ and ϵ_W^L, we get

$$BW^\theta \left(-\frac{\alpha A \theta \left(BW^\theta + C \right)^{\alpha - 1}}{W} + \theta + 1 \right) + C = 0. \tag{16}$$

Solving for A gives us

$$A = \frac{W^{1-\theta} \left((\theta+1) BW^\theta + C \right) \left(BW^\theta + C \right)^{1-\alpha}}{\alpha B \theta}. \tag{17}$$

To obtain the passthrough elasticity, we take derivatives with respect to A on both sides of Equation (16), 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 (17). 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.2.5 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

$$\epsilon_A^w = \frac{dW}{dA}\frac{A}{W} = \frac{dW}{dL}\frac{L}{W}\frac{dL}{dA}\frac{A}{L} = \frac{\epsilon_A^L}{\epsilon_w^L}, \tag{18}$$

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 Two-sided Fixed Effect Regression

F.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

$$w_{ijt} = \alpha_i + X_{it}\Gamma_t + \psi_{j(i,t)t} + \xi_{ijt}, \tag{19}$$

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 maybe different in 2000 compare to in 1990. Heuristically, the identification can be achieved in three parts: the covariates 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) (AKM) 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 labor earnings of two workers, j and i, that work in firm j in period t and firm k in period $t-1$,

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

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. [49]

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:[50]

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

where the second and fourth line use $\mathbb{E}\left[\xi_{ijt}\right] = 0$. 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 Xs 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 effects 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 identification. However, having multiple job information available helps us to get better estimates as it increases the effective number of switchers. To see this is the case, assume that individual i

[49] 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.

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

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

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

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).

F.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,

$$Var\left(w_{ijt}\right) = \underbrace{Var\left(\alpha_i + \Gamma' X_{it}\right)}_{\text{Worker Component}} + \underbrace{Var\left(\psi_{j(i,t)t}\right)}_{\text{Firm Component}} + \underbrace{2 \times Cov\left(\alpha_i + \Gamma' X_{it}, \psi_{j(i,t)t}\right)}_{\text{Wage Sorting Component}} + \underbrace{Var\left(\xi_{ijt}\right)}_{\text{Residual}},$$

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 in terms of their wages, that is, how much of the variation in wages is due to the fact that high quality workers–as measured by $\alpha_i + \Gamma' X_{it}$—are hired by high-wage firms—as measured by $\psi_{j(i,t)t}$.

Table A.7 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 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 accounts 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 that 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.

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 A.7.

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 A.7 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 full-sample estimates going forward, confident that they do not suffer from limited mobility bias.

Table A.7 – 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:									
$\alpha_i + X_{it}\Gamma$	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%
$2 \times Cov\left(\psi_{(i,t)j}, \alpha_i + X_{it}\Gamma\right)$	1.0%	1.0%	1.3%	1.4%	1.5%	1.6%	1.6%	1.2%	1.1%
$Corr\left(\psi_{(i,t)j}, \alpha_i + X_{it}\Gamma\right)$	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 A.7 presents the results of our wage decomposition exercise and analyses the effects of limited mobility bias in our estimates. Specifically, it shows how the contribution of worker's 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 which have below 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 estimations are obtained by pooling data from 1991 to 2010.